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1 WELCOMING REMARKS
 2 - - - - -
 3 MR. VITA: Okay, let's get started, everybody.
 4 Good morning. My name is Mike Vita. I'm the Deputy
 5 Director for Research here at the FTC's Bureau of
 6 Economics. Thanks to you all for coming, and welcome
 7 to the Eleventh Annual FTC Annual Microeconomics
 8 Conference, where we attempt to combine cutting-edge
 9 academic research with discussions of real-world
 10 policy problems. As always, we're grateful to
 11 Northwestern University and the Searle Center for
 12 their continued cosponsorship of this conference.
 13 For those of you who are from other
 14 institutions, a few words about us here at the FTC.
 15 As you probably know, the FTC is an independent agency
 16 that, along with the Department of Justice, enforces
 17 the antitrust laws. Our other major mission here at
 18 the FTC is enforcement of federal consumer protection
 19 law. These enforcement missions are supported by the
 20 FTC's Bureau of Economics, which is a group of about
 21 80 Ph.D. economists, which makes it one of the largest
 22 groups of applied microeconomists in the Federal
 23 Government.
 24 At the FTC, we believe very strongly that these
 25 twin enforcement missions reinforce and complement

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1 each other. Competition, we think, is most effective
 2 when consumers are making well-informed choices and
 3 decisions, and consumer protection works best when
 4 consumers have real alternatives.
 5 Today's conference, like its predecessors,
 6 helps ensure that the FTC's actions are informed and
 7 guided by the best possible economic analysis. So I
 8 think, as we always do, I think we'll have a fantastic
 9 conference this year. In addition to the usual
 10 cutting-edge papers that we always feature, tomorrow
 11 we have a panel discussion on the estimation of
 12 markups, a topic that's become pretty important in
 13 antitrust circles these days.
 14 Before the first panel starts, just a few
 15 acknowledgments and then a few official announcements.
 16 First, let me take a moment to thank Ted Rosenbaum,
 17 Nathan Wilson, and Alex Avramov of the FTC for their
 18 hard work in putting together the conference; Julie
 19 Carlson, Antara Dutta, and Nathan Petek for their
 20 assistance to the scientific committee; to a large
 21 group of BE economists, who I won't mention by name,
 22 who gave feedback on the various submissions that we
 23 received; and to our scientific committee of
 24 academics, David Besanko of Northwestern, Katja Seim
 25 of Penn, and Ali Hortasçu of Chicago.

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1 Ali, if you're in the audience, I hope I
 2 pronounced your name right. I got multiple opinions
 3 about that. They were all different.
 4 I also want to thank our wonderful BE
 5 administrative team, who always do incredible work
 6 behind the scenes to ensure that the conference comes
 7 off seamlessly, Maria Villaflor, Kevin Richardson,
 8 Neal Reed, Constance Herasingh, Priscilla Thompson,
 9 and Tammy John.
 10 On that note, on the administrative note, right
 11 at the moment we do not have WIFI information for you
 12 guests, but we will soon. So that will be -- we will
 13 update that.
 14 Then I guess I'm supposed to -- Ted says I have
 15 to read some important legalese that we're compelled
 16 to talk about. First, silence your mobile phones; I'm
 17 sure you've all done that. Please be aware that if
 18 you leave Constitution Center -- that's this
 19 building -- for any reason during the workshop, you
 20 will have to go back through security screening again.
 21 This is in bold. Most of you received a
 22 lanyard with a plastic FTC Event security badge. We
 23 re-use these, so when you leave for the day, please
 24 return your badge. You know, money's tight. We can't
 25 replace those.

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1 If an emergency requires that you leave the
 2 conference center but remain in the building, follow
 3 the instruction provided over the building PA system.
 4 If an emergency occurs that requires the evacuation,
 5 an alarm will sound, and just follow everybody else.
 6 If you notice any suspicious activity, please
 7 alert building security. I don't know if that
 8 includes suspicious activity that takes place during
 9 the panels, but any other kind of suspicious activity,
 10 alert building security.
 11 Lastly, please be advised -- oh, importantly,
 12 restrooms are located in the hallway just outside the
 13 conference room. And last, please be advised that
 14 this event may be photographed, webcast, or recorded.
 15 By participating in this event, you are agreeing that
 16 your image and anything you say or submit may be
 17 posted indefinitely at ftc.gov or on one of the
 18 Commission's publicly available social media sites.
 19 So it will live forever. So choose your words
 20 carefully.
 21 Okay. That, I think, concludes that. So let
 22 me just turn it over to Julie Carlson, who will
 23 introduce today's first panel. Thank you.
 24 (End of session.)
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1 PAPER SESSION:
 2 PUBLIC COMMUNICATION AND
 3 COLLUSION IN THE AIRLINE INDUSTRY
 4 - - - - -
 5 MS. CARLSON: Welcome. It's my pleasure to
 6 open our first session, which was organized by David
 7 Besanko of Northwestern. So we will have two papers
 8 in this session, and each presenter will have 25
 9 minutes to present, and then after each presentation,
 10 we will have a ten-minute discussion, and then we will
 11 have about ten minutes left over for questions from
 12 the audience.
 13 So our first paper is by Gaurab Aryal from the
 14 University of Virginia, who will be presenting Public
 15 Communication and Collusion in the Airline Industry.
 16 MR. ARYAL: Thank you. Thanks to the organizer
 17 for accepting the paper. This is joint work with
 18 Federico, who is at the -- he is also at Virginia, and
 19 Ben, who was a grad student but now at Cornell. So
 20 this paper is about public communication -- I'll
 21 explain exactly what that is -- and how that can
 22 facilitate collusion; in particular, the industry that
 23 we look at is the airline industry.
 24 So just the big picture. So, you know, the
 25 idea that -- so there are two kind of competing

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1 institutions or laws that we look at. One is
 2 antitrust, which forbids firms from communicating with
 3 each other in order to kind of deter collusion, but on
 4 the other hand, you have financial regulations, which
 5 tries to promote transparent communication, all right?
 6 So the question that we are interested in is
 7 what if the second one helps evade the first one,
 8 okay? What if these transparency laws facilitate
 9 collusion? This is actually pretty well thought out
 10 by the OECD, so it says that information exchanges can
 11 offer firms point of coordination of focal points. Of
 12 course, these are all abstract terms. What is focal
 13 point? What is coordination? So we tried to find an
 14 empirical evidence of that in the data.
 15 Ultimately, I mean, of course, we don't address
 16 this question in the paper, but ultimately we are
 17 interested, of course, as empirical IO-ists is what
 18 kind of information should firms be allowed to share
 19 in public, okay? And we leave that question as it is.
 20 So the main objective of today's talk and the
 21 paper is to ask the following question: Do managers
 22 in legacy U.S. airlines use their earnings call to
 23 communicate with other legacy airlines in reducing the
 24 number of seats sold in the domestic U.S. airline
 25 market?

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1 Okay, and in particular, when we talk about
 2 communication, we focus on this concept of capacity
 3 discipline, okay? So any word related to capacity
 4 discipline, that will be what we will call
 5 communication, of course. Just to give -- why is
 6 information important or communication important? A
 7 priori, you think that given, you know, the nature of
 8 the business, stochastic demand, kind of difficult to
 9 monitor each other, you think that collusion among
 10 airlines would be difficult. That's the a priori
 11 thought.
 12 But, of course, there's these three really
 13 super papers by Yu Awaya and Vijay Krishna, one is in
 14 AER, the first one, and what they show is that if you
 15 have private monitoring, meaning I can only observe my
 16 own action, but you can sense some cheap-talk, some
 17 information out, then they show that in many cases you
 18 can do better than Nash, okay, meaning you can sustain
 19 a collusive outcome.
 20 And so what we are going to do is kind of think
 21 about this in sort of like a reduced-form way, is
 22 giving -- taking this as a benchmark theory model, we
 23 are going to try to see if there is any evidence of
 24 this in the airline industry.
 25 So in terms of the data and the methodology,

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1 what do we do? We basically build a data set of
 2 public communication. We read through all the
 3 earnings calls. And so every quarter, publicly traded
 4 companies hold earnings calls where they communicate
 5 about the future strategies about the companies, and
 6 all of these are transcribed and recorded. So we
 7 basically read all of them and try and determine which
 8 of the -- which quarter's earning calls were
 9 pertinent, pertinent meaning there was some
 10 communication about capacity discipline.
 11 And then once we have figured that out, we try
 12 to estimate or actually we estimate the causal effect
 13 of communication -- I'll explain exactly what that
 14 is -- on the number of seats made available in the
 15 domestic market, okay?
 16 So there are some issues. So exactly how do we
 17 approach that? The first is we -- the first thing we
 18 do is we ask, do carriers change capacity after
 19 discussing capacity discipline? So think about
 20 quarter one, where everybody, all the legacy carriers
 21 in a market, a market defined by airport-to-airport
 22 pairs, mention capacity discipline. Then we look at,
 23 subsequently, does that lead to a reduction in the
 24 number of seats being sold in the following quarter?
 25 And the answer is yes.

13	<p>1 So we find that, on average, the airlines 2 reduce about 1.45 percent, and that's a -- you know, 3 in terms of how big that number is, in general, the 4 average change in capacity is about 3.5. So it's a 5 pretty big number. 6 The other thing that we have to kind of 7 determine is that is this a collusion or is this just, 8 you know, the airlines using these earning calls to be 9 more transparent about their strategies? And if they 10 are, indeed, just being transparent about the 11 strategies, then the fact that we find a reduction in 12 capacity does not necessarily mean that they are 13 coordinating, okay? 14 And so if that was the case, then we look at 15 things like, you know, imagine the airlines were the 16 only one who mentioned the word "capacity discipline," 17 while everybody else serving the market do not, then 18 do we see a reduction? 19 If it was serving the purpose of just being 20 transparent, then we would imagine there to be a 21 reduction, but we find none, okay? And we also then 22 look at other ways; for example, we also look at what 23 if everybody, other than -- except -- so if there are 24 five airlines serving a market, suppose four out of 25 five talk and mention capacity discipline? Do we see</p>	15	<p>1 find that there is a significant reduction in capacity 2 whenever they talk about communication, okay? I'll 3 explain all of these in detail. 4 For the remainder of the talk, I'll just 5 briefly talk about the data. I will not go into the 6 detail. There are two basic parts of the data. One 7 is the transcript data, which is what we've collected 8 from the earnings call, and the second is the usual 9 airline data, which is the T-100 and DB1P. We augment 10 the airline data by buying -- so we augment that with 11 an OAG data, which allows us to take care of the 12 differences between the ticketing carrier and the 13 operating carrier. So it's possible that if two major 14 airlines subcontract to a local one, the T-100 is not 15 going to capture that part, so we know exactly who the 16 regional carrier is contracting with, okay? 17 I'll talk about the empirical analysis. As I 18 said, I'll address these two or three concerns that I 19 just brought up, and then I'll conclude. This is the 20 data on transcripts. So each row is an airline, so 21 there are 11 airlines. Each column is a quarter. So 22 we start from the last quarter, 2002, all the way to 23 2016, all these different colors. 24 The colors that we should focus on is the light 25 green one. So that means that -- say, if I look at</p>
14	<p>1 a reduction? 2 If, indeed, they were just serving their 3 transparency problem, then we should have seen a 4 reduction, but we don't see any reduction, all right? 5 So these are some sort of not direct but kind of 6 indirect evidence that it seems like this capacity or 7 these communications are not serving the purpose that 8 they were supposed to, okay? 9 The third is we also have to deal with some -- 10 because we are using words and text, there might be 11 some other words that are connected and we miss out on 12 that, so we look at that as well. And the other issue 13 is, as I'll explain in a bit, the way we define 14 communication requires some market structure. So we 15 know from previous literature that market structure 16 can be endogenous, depends on some other unobservable 17 that is not accounted for in the data. So the 18 question is, should we then be concerned about these? 19 And we addressed this. 20 First, as far as the communication part is 21 concerned, we look at -- we do some conditional 22 exogeneity test, and we find that our result is 23 consistent. And we also do IV, actually control 24 function approach, to try and address the fact that 25 the market structure might be endogenous, and we still</p>	16	<p>1 one particular -- so, if -- take Southwest, for 2 example, at the bottom. Quarter four, 2002, it's 3 green. That means that for that quarter we have 4 collected the transcript data, okay? And other colors 5 are different reasons for which we do not have the 6 transcript data. 7 For example, if they are privately owned, we 8 don't have it. If they're before -- just after 9 merger, we don't have it. And then in some cases, the 10 black ones, we don't know -- we don't have the data, 11 but we don't know why the data is not available. When 12 we do the regression, we try to control for that as 13 well, okay? 14 So not all of these green ones are the ones 15 where the airlines talk about capacity discipline, 16 okay? So how do we -- just a one-page thing about 17 text to data. So what do we do? Basically we take 18 all these text documents and then we use the natural 19 language processing and we try to flag any quarter in 20 which the word -- by "word," I mean the semantic of 21 "capacity discipline" -- shows up, okay? So it's 22 possible that the airlines do not always use exactly 23 "capacity discipline," but as long as they imply 24 capacity discipline, we pick it up. 25 We do a bunch of robustness on that. We verify</p>

17	<p>1 ourselves. We hired an independent RA to read through 2 this completely carefully and give us the data the way 3 the RA thought about it, so we can -- so we 4 double-checked everything. Everything is in the 5 paper. 6 And in some cases, when it's not absolutely 7 clear what's happening, we read the transcripts 8 ourselves. Three of us read independently, and we try 9 to, you know, see if we all agree that this is 10 pertinent, i.e., this is about capacity discipline, or 11 this is not pertinent, okay? 12 So to just give you examples of how these words 13 "capacity discipline" crop up, this is U.S. Airways. 14 Main line passenger revenue were up by 2.1 billion, 15 da-da-da, and continued industry capacity discipline. 16 So they are basically trying to say that our revenue 17 went up because there was an industrywide capacity 18 discipline, so everybody were disciplined when they 19 were choosing the capacity. 20 Or the CEO of Delta, you have heard us 21 consistently state that we must be disciplined with 22 capacity. So as far as we're concerned, even though 23 it's not exactly capacity discipline, the second one, 24 it pertains to the same notion of capacity discipline. 25 So we picked both of these instances.</p>	19
18	<p>1 area and D.C. area. So we also have that result in 2 the paper. Things become a little bit involved, you 3 know, because there's inter-airport substitution, but 4 for the talks today, I am going to just focus on 5 airport pair. 6 So this is the construction of the variable of 7 interest. This is what we will define to be 8 communication. So we call that capacity discipline. 9 So capacity discipline in market m, t is a product of 10 two dummy variables. The first one is talk-eligible. 11 By talk-eligible, we mean that there have to be at 12 least two legacy carriers in the market for there to 13 be even a question about communication, so we need the 14 talk-eligible. That's where the market structure 15 becomes important, and that's where the possible 16 endogeneity will also come. 17 And the second part is all of these legacy 18 carriers, at least two of them, there are at least two 19 of them, all of them are using capacity discipline in 20 the previous quarter. So if both of these are 21 satisfied, then we take the dummy, and that's when we 22 call there is a communication among these airlines, 23 okay? 24 And so this is the basic regression model, very 25 simple. On the left-hand side, we have log of seats</p>	20

21	<p>1 by Airline J in Market M in Period T. We regress on a 2 bunch of variables, but the object of interest, the 3 variable of interest is capacity discipline, which is 4 the first one, the coefficient beta naught. We also 5 control for -- you know, because -- you know, we allow 6 for -- we control for various other factors that could 7 influence the decision or the seat. 8 So, for example, we treat markets where at 9 least there are two versus only one legacy carrier as 10 separately, so that's the talk-eligible. Remember 11 that the talk-eligible, which is the beta one, is also 12 in the capacity discipline, okay? So think about the 13 capacity discipline as an interaction between 14 talk-eligible and everybody communicating. 15 We also control for monopoly. We don't know 16 why the datas were missing, so we also control for the 17 missing reports, those black dots in the picture, and 18 we have a bunch of fixed effects. We have airline 19 market fixed effects, airline year quota fixed effect, 20 origin fixed effect, destination, time fixed effect. 21 So basically, what are we doing with the fixed 22 effect? The intuition is that we are trying to 23 control for any other demand-related shock that would 24 affect the left-hand side variable, okay? And so our 25 null hypothesis -- so we are interested in the -- in</p>	23	<p>1 what I just said in a bit, are carriers just being 2 transparent with the investors about future plans? 3 And so if this is, then there is really no reason for 4 concern and this is not about capacity discipline 5 helping airlines coordinate or collude. 6 The second is conditional exogeneity. There 7 could be some unobserved factors that is affecting and 8 driving our result, especially related with the way in 9 which we talk about the text, okay? 10 And the third one, the third concern is the 11 market structure being endogenous. The fact that a 12 market is talk-eligible, meaning that at least two 13 legacy carriers, or three or four, could itself be 14 endogenous, which leads that the way in which we 15 define the capacity discipline would be endogenous, 16 and so we look at -- we address this by using a 17 control function, okay? 18 So just a quick result of what we do. So we 19 asked the following question: Do legacy carriers 20 reduce capacity when they're the only carrier in the 21 talk-eligible market talking? So if you are the only 22 one -- suppose there are two airlines, two legacy 23 carriers, and you are the only one talking, and you 24 say, "I want to reduce capacity, I need to be 25 disciplined," and this was a communication to the</p>
22	<p>1 the est beta naught (phonetic) and what is the sine of 2 the beta naught. 3 So this is the -- so just look at the first 4 column for the time being, and the object of interest 5 is the first variable, and we see that whenever the 6 airlines communicate, they reduce the capacity by 1.49 7 percent, and any statistically significance. And if 8 you break -- you know, there are various ways in which 9 you can decompose these effects. If we -- I am going 10 to go focus on this one in view of the time. 11 So imagine -- so when we think about a market, 12 a market is a mixed market if it's served by both the 13 legacy carrier and the local carrier, and we decompose 14 in the market what is the effect of communication on 15 the capacity of -- you know, of the legacy carriers 16 versus local carriers, and we see that, in fact, the 17 local carriers do not have any effect. So the second 18 one is, in fact, insignificant. The first one, the 19 legacy, is -- becomes more stronger, okay? 20 So in a sense the summary of this is that there 21 is some evidence that whenever airlines talk about 22 capacity discipline, they do, indeed, reduce capacity, 23 and it's only the legacy carriers who are doing that. 24 Possible concerns? As I said, financial 25 transparencies, what we mean by that, just to repeat</p>	24	<p>1 investor, you would see a subsequent reduction, but we 2 find none. So the first one -- sorry, the first row, 3 only J talks, we find that, in fact, the effect is 4 positive. So they don't reduce capacity. 5 Second, what about monopoly markets? So 6 imagine a market where you're the only guy selling and 7 offering the air service, and you say, "I want to 8 reduce capacity," do you see any reduction? The first 9 one -- the first row, you see that there is reduction. 10 In fact, it's positive. 11 The third one we do is suppose -- as I said, 12 we -- by definition, you know, if you look at the 13 Awaya/Krishna paper and you repeat it again, the 14 communication involved everybody talking, and suppose 15 that only one person is left out. Suppose N minus 1 16 people talk, but 1 percent doesn't talk, what happens 17 to -- what is the effect of that on capacity 18 discipline? 19 If -- again, if it was all about transparency, 20 then we should have seen some reduction, whatever the 21 size might be, but we find, in fact, there's a 22 positive increase. So this seems to suggest that 23 there is something happening with the capacity 24 discipline that needs more thought. 25 Okay, so just to summarize, we find that</p>

25	<p>1 capacity -- that carriers do not reduce capacity when 2 they unilaterally discuss capacity or when it's a 3 monopoly market or if N -- you know, N minus one 4 people or airlines in the market discuss the capacity 5 discipline, but only one does not. 6 Conditional exogeneity, so this is a little bit 7 involved. So suppose -- what are we worried about is 8 that the way that we define and choose the word 9 "capacity discipline," it could be that we're worried 10 about that can there be other words that are 11 positively correlated with the capacity discipline but 12 negatively correlated with the log seats, okay, and 13 that's what is basically driving it, because we are 14 not controlling for that, and that's the big worry, 15 because, of course, we don't know what exact words 16 these guys are using. It could be that we're missing 17 some other words, that it's left over, and it's not 18 about capacity discipline. That's something that we 19 would have to worry. And so to address that, we 20 follow a test motivated by Hal White and Corrine 21 Chalak. And so I am going to skip all of this. 22 Basically what we want to do, we want to -- we 23 look at the text data, and we found -- and we look for 24 any word that is related with capacity discipline 25 semantically, and then we ask, suppose now you</p>	27	<p>1 look at the distance from an airport to the hub, which 2 is a proxy for the cost of entering, and use that 3 distance -- so we predict what is the -- what is the 4 likelihood of a market being talk-eligible, and then 5 we redefine our communication. 6 I am going to go -- skip all these pictures. 7 And so when we use the -- so basically just the 8 control function, we find that the capacity discipline 9 now with the control function is still significant, 10 slightly smaller in size. So it's 1.14 instead of 11 1.45. 12 I think I just hit the button, so that's the 13 conclusion. Thank you. 14 (Applause.) 15 MS. CARLSON: Next we will have Gloria Sheu, 16 from the U.S. Department of Justice, Antitrust 17 Division, to give a discussion. 18 MS. SHEU: Okay. Well, first, I want to thank 19 the organizers for inviting me to do this discussion. 20 I had a lot of -- I really enjoyed reading this paper. 21 I thought it was really interesting on an important 22 subject. I also have to start with the normal 23 disclaimer, that the views I am going to express today 24 are entirely mine and should not be purported to 25 reflect those of the U.S. Department of Justice.</p>
26	<p>1 introduce that word that is related to capacity 2 discipline, and it occurs as frequently as capacity 3 discipline, and you include that as an additional 4 regressor. 5 And we would expect -- if our capacity 6 discipline is capturing everything that we think it's 7 capturing, then the coefficient on that should be 8 non-negative, right, because that's what we worry 9 about the most, and if it is not negative, it should 10 be insignificant, right? 11 And so when we look at this, we -- this is -- 12 this is what we find. I have one minute. So six 13 words which satisfy -- they will use as frequently as 14 "capacity discipline," but when you put it as an 15 additional regressor, the coefficients are all 16 positive, except for "slow." And it's a little bit 17 big, and -- but the thing that is reassuring for us, 18 at least, is that the capacity discipline in all of 19 these regressions have similar coefficients, so it's 20 kind of stable, even if you add and throw in all these 21 variables, which might be semantically related. 22 And, okay, market structure, next, thinking 23 about the fact that the talk-eligible is correlated. 24 So we use -- I am going to go fast -- so we define 25 hubs as -- hubs for each airline each month, and we</p>	28	<p>1 Okay. So as you just heard Gaurab discussing, 2 I think this paper has two main parts. The first is 3 the authors, they document an interesting empirical 4 finding, which is that when you have two legacy 5 carriers or actually all the legacy carriers in a 6 market discussing capacity discipline in their 7 earnings calls, you then see them actually decrease 8 the number of seats in overlap markets. Then, the 9 second part of the paper is to go on and argue that, 10 based on that, this is evidence of collusion between 11 those legacy carriers. 12 So given that that's the structure of the 13 paper, I think the authors rightly go through a lot of 14 work to try and say, hey, there's not an alternative 15 explanation, like our story that this is collusion is 16 what you should believe, and overall, I found that 17 compelling. I thought it was particularly helpful to 18 see cases where this pattern was not happening. So, 19 for example, low-cost carriers did not appear to be 20 participating in the markets where not everybody was 21 discussing this, as Gaurab was just saying. That's 22 not -- does not appear to be affected. So that kind 23 of, like, maps out, like, exactly what it is we're 24 talking about here, but nonetheless, it's, of course, 25 difficult to prove a negative. I think that's typical</p>

29	<p>1 of this type of paper.</p> <p>2 As we saw, there was a lot of kind of different</p> <p>3 steps and additional work that the authors did to try</p> <p>4 and cross off as many of the alternative explanations</p> <p>5 as possible. Today, I think rather than add to the</p> <p>6 stack of things that they've already tried and I'm</p> <p>7 sure that they're considering trying, I want to step</p> <p>8 back a little bit and discuss a little more, like, the</p> <p>9 wider antitrust context for this type of research.</p> <p>10 So one reason why I really like this paper is I</p> <p>11 think it's super important for people to work on</p> <p>12 research related to collusion and coordinated effects</p> <p>13 of mergers. On the one hand, we see that I think</p> <p>14 antitrust practitioners -- so folks who work as</p> <p>15 experts in, for example, merger cases -- and courts,</p> <p>16 finders of facts, have converged or somewhat converged</p> <p>17 to a generally accepted set of ways of thinking about</p> <p>18 the unilateral effects of mergers.</p> <p>19 We see, for example, similar types of merger</p> <p>20 simulations come up in a lot of cases, and that's</p> <p>21 great because it means when you're looking at a new</p> <p>22 case, you have some common ground to think about.</p> <p>23 You're not starting from zero with your analysis.</p> <p>24 On the flipside, for coordinated effects of</p> <p>25 mergers and collusion and non-merger cases, I think</p>	31	<p>1 collusion that they're identifying here is that it's</p> <p>2 kind of partial, and that could be interesting to</p> <p>3 rationalize in a model, and there are models out there</p> <p>4 that deal with this, but in this particular instance,</p> <p>5 what we have to have is a model that would have only</p> <p>6 certain geographic markets being affected at any</p> <p>7 particular time, so specific overlap markets where</p> <p>8 they're communicating. Some firms are not</p> <p>9 participating in all time periods, so some of them are</p> <p>10 not saying "capacity discipline" at all times. And</p> <p>11 some firms appear to be entirely excluded, so the</p> <p>12 low-cost carriers are not involved at all.</p> <p>13 So you need a model where somebody or a group</p> <p>14 of firms find it in their interest to collude, but</p> <p>15 they don't want to, like, collude too much, right?</p> <p>16 They don't want to do it all the time, for all time</p> <p>17 periods and for all market conditions, so there's got</p> <p>18 to be some sort of friction in there.</p> <p>19 So just breaking that down a little bit more,</p> <p>20 for the geographic markets, like, why were these</p> <p>21 particular markets chosen would be an interesting</p> <p>22 question, and I would think that in the model that</p> <p>23 would underpin this, you might find that there was</p> <p>24 some sort of incentive compatibility constraint that</p> <p>25 was -- meaning that certain markets got excluded.</p>
30	<p>1 it's way more wide open. There's not quite as, you</p> <p>2 know, a generally accepted set of models or empirical</p> <p>3 tools, and it's not that these cases don't get brought</p> <p>4 and that people don't look at these things. That</p> <p>5 definitely happens, but at least from my experience,</p> <p>6 the cases that I've seen, a lot of the work ends up</p> <p>7 being very specific to that particular matter, and</p> <p>8 it's -- and then the work is kind of, like, difficult</p> <p>9 to transport into another situation, which then, if</p> <p>10 you're looking at some other potential matter, you're</p> <p>11 kind of starting from zero, and you might not be on</p> <p>12 the same page as other people who are thinking about</p> <p>13 the same investigation.</p> <p>14 So this is largely an empirical paper. Gaurab</p> <p>15 referred to some of the existing literature that --</p> <p>16 theory literature that could underpin it, but I think</p> <p>17 it's helpful to think about that some more. I think</p> <p>18 some -- in the paper as it's written now, I think</p> <p>19 maybe some more, like, light exposition along those</p> <p>20 lines -- that would be my one comment -- would help</p> <p>21 fix ideas on this a bit more, but I am not suggesting</p> <p>22 some sort of separate theory or extrastructural</p> <p>23 estimation, as that would be an entire paper unto</p> <p>24 itself.</p> <p>25 But what I found really interesting about the</p>	32	<p>1 The thought process here would be, all right,</p> <p>2 some -- maybe they would have wanted other potential</p> <p>3 overlap markets to be included, but for whatever</p> <p>4 reason they didn't all communicate, and maybe that was</p> <p>5 because maybe they didn't want to include it or maybe</p> <p>6 it was actually in -- somebody would have wanted to,</p> <p>7 but if they had done that, they would have induced</p> <p>8 cheating. That would be one thought process that</p> <p>9 could rationalize that.</p> <p>10 Stepping even farther back, like, generally,</p> <p>11 what kind of punishment would you set up to get this?</p> <p>12 Some measures of capacity are publicly available. The</p> <p>13 data was used in this paper. I think that these</p> <p>14 airlines are reasonably well informed about what's</p> <p>15 going on around them, so monitoring might not be a</p> <p>16 huge issue. So why at some points aren't they talking</p> <p>17 about capacity discipline? Is it a situation where,</p> <p>18 you know, they all just decided we're not going to do</p> <p>19 this right now, or is it that the scheme broke down</p> <p>20 and they went into a punishment phase. If it's the</p> <p>21 latter, how did they start up again, right? So that</p> <p>22 would all have to be built into the structure here.</p> <p>23 And then another really interesting thing is we</p> <p>24 had these LCCs hanging out here. You see in the</p> <p>25 antitrust literature, it talks about mavericks that</p>

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1 don't participate in a collusion scheme. Could these
2 have been mavericks? It's possible. That would be a
3 situation where the legacy carriers would have wanted
4 them to participate but couldn't get them to for
5 whatever reason, and the LCCs might have actually
6 prevented additional collusion or the collusion that
7 happened from being more successful.

8 The flipside could be that these LCCs just
9 weren't that good substitutes or weren't that high a
10 competitive constraint for these legacy carriers, so
11 they just didn't bother dealing with them. I could
12 imagine that the answer would depend on the market and
13 maybe on the LCC they were talking about. So there
14 could be some variation there that might be
15 interesting. And I think that, you know, the idea of
16 a maverick is something that pops up a lot in
17 antitrust contexts, but trying to actually, like, look
18 at something empirically on that actually might be
19 really helpful.

20 And, of course, there's just the wider, really
21 big-picture, general questions. Any time we're
22 looking at antitrust relevant research, there's a
23 question of did mergers play a role. We definitely
24 had a bunch of airline mergers in the not-too-distant
25 past. I mean, this could be some additional empirical

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1 work, and the paper just looked specifically at what
2 happened around those. Did the firms involved change?
3 Did the markets involved change? Did the amount of
4 talk change? Did this bring certain firms into the
5 fold? Honestly, just some empirics around that itself
6 might be interesting, and then that could also say,
7 okay, maybe that would be something that would be
8 interesting to model.

9 And then, of course, the million dollar
10 question is, what happened to prices and consumer
11 welfare? Again, that would be something that you'd
12 need some structural modeling and estimation to get
13 to, but that is really the question that we're after
14 when we're thinking about looking at collusion and,
15 for example, making a case as to why something might
16 be prohibited conduct in a court of law.

17 (Applause.)

18 MS. CARLSON: So I'll ask Gaurab to come back
19 up to the podium. We will have about ten minutes for
20 questions. Alex and Jenn in the back there are
21 wandering around with microphones. So if you would
22 like to ask a question, just flag one of them and
23 we'll have some discussion.

24 MR. BRUESTLE: Steven Bruestle, Federal
25 Maritime Commission. This reminds me of a growing

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1 antitrust literature on the effect of the same
2 investor owning shares in multiple competitors.
3 Investors like to diversify their portfolios, yet this
4 can encourage collusion.

5 Do you have a way of controlling for this?
6 Perhaps overlapping owners impact the coordinated
7 effect that you found.

8 MR. ARYAL: We did look at the timing, meaning
9 who initiates the questions that leads to the answer
10 that contains capacity discipline in the hope that we
11 could probably try and tie the analyst, let's say,
12 back to the real owners, and we didn't find any effect
13 of that at all, but we did not pursue seriously, to be
14 honest, the line of common ownership yet. But we are
15 aware that that's something that's happening and,
16 yeah, we don't know really.

17 MR. BRUESTLE: Okay, fair enough.

18 MR. RASMUSEN: Hi. I'm Eric Rasmusen, Indiana
19 University. I wonder if you could tell us more about
20 earnings calls. Do they happen every quarter? And
21 what order do they occur in? Is it the same airline
22 who goes first? That sort of thing would be really
23 interesting to know about.

24 MR. ARYAL: Right. So it happens every
25 quarter, and as I said, we did try to look at the

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1 timing issue. It didn't matter if Delta was the first
2 to do the earnings call in that particular quarter.
3 Is that what you mean?

4 MR. RASMUSEN: Oh, yes. Oh, and also, do
5 analysts ever bring up capacity discipline?

6 MR. ARYAL: So that's kind of related to what I
7 was just saying, that analysts do bring up sometimes
8 the capacity discipline, and we do try to look at if
9 there was any -- you know, if we could see some
10 pattern, but we did not find any pattern, either when
11 the analysts bring it up or one of the legacy carriers
12 is the first one to bring it up.

13 The idea that we had was that there's this new
14 paper that is coming in AER where they show, in
15 Australia, that BP kind of leads others to collude and
16 follow them through, and we did try to see if there
17 was any evidence of any particular airlines doing
18 that, but we didn't find any.

19 And to be honest, I guess, the idea of
20 cheap-talk and communication with a leader is also --
21 we don't know how to conceptualize that idea. So,
22 theoretically, we don't know what a model -- you know,
23 can there be, you know, a theory model where a leader
24 leads others through the cheap-talk, you know, where
25 monitoring might be a little bit messy or at least

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1 with the lag, so -- but yeah, thanks.
 2 AUDIENCE MEMBER: Hello. So I guess the main
 3 concern I guess is that when these four -- when all
 4 the legacy carriers talk, you know, it's a big
 5 negative demand shock. I guess that's one way of
 6 thinking about this. And then one way of reading the
 7 results is that those markets where at least two
 8 carriers are present are maybe more cyclical, more
 9 affected by those aggregate demand shock, and, you
 10 know, that -- I mean, you know, if, for instance, you
 11 figure Philadelphia is probably less cyclical than
 12 LAX, LaGuardia, and that might be what's going on, and
 13 one way of accounting for this would be to add more
 14 controls, I mean, for those things, and I'm wondering
 15 if you --
 16 MR. ARYAL: So, yeah, add more local controls
 17 or --
 18 AUDIENCE MEMBER: Well, I mean, you could
 19 easily add those aggregate demand shock controls.
 20 MR. ARYAL: Sure. So at least the first part,
 21 we do -- because, you know, we also control for the
 22 talk-eligible, so that takes care of maybe the first
 23 part of your point, that really we are interested in
 24 the interaction of who's serving and if they are all
 25 talking versus who is serving, so that takes care of

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1 that point, but we did not add any global -- you know,
 2 maybe we could use past -- something like, you know,
 3 past demand or past load factor or something like that
 4 to get at.
 5 We did have a time trend at the -- at the
 6 airline and the market level, so that also takes care
 7 of if -- you know, this is -- the thing -- the way we
 8 are thinking about it is that if the demand is
 9 growing at 3 percent, does the capacity also grow at 3
 10 percent or not when they're talking? I think that's
 11 how we interpret that. So it's -- so we have to think
 12 about exactly how the identification would work, but
 13 that's something that we could think through. Thanks.
 14 MS. FORBES: Hi. Silke Forbes, Tufts
 15 University.
 16 I was wondering if you could talk a bit about
 17 market definition. You said -- you talked about the
 18 results using airport pairs.
 19 MR. ARYAL: That's correct.
 20 MS. FORBES: What happens when you use city
 21 pairs instead?
 22 MR. ARYAL: So in city pairs -- so what matters
 23 is whether you have two or three airports make a
 24 difference, and so, you know, we tried to look at why
 25 is there a difference between two and three. So, for

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1 example, if you have three, then there is no effect,
 2 but if there are two, then we find that there is an
 3 effect. The closest that we could come up with was
 4 the hoteling thing, where, you know, things are a
 5 little bit less stable when you have three. I don't
 6 know, that's just a -- I'm stretching here, but we --
 7 yeah, with three, something happens, and we don't find
 8 any effect. You know, we do that in the paper, so
 9 it's -- thanks.
 10 MR. LAU: Hi. My name is Yan Lau from the FTC.
 11 I just noticed that you might have tried this before,
 12 but have you tried -- like, you have a log
 13 specification, but if you were just to go with a
 14 linear specification, you can actually put in all the
 15 zeros of the dependent variable, and then you could
 16 potentially get at market entry and exit, because
 17 right now I think what you're doing is you're throwing
 18 away all the routes where an airline has zero seats,
 19 zero capacity, and so if you put in all the zeros and
 20 you're willing to get away from the log/linear
 21 specification, then you can see whether people exit or
 22 enter the market based on capacity discipline.
 23 MR. ARYAL: Okay. We did not -- we did not
 24 do -- we never thought about linear specifically at
 25 all, to be honest, but I have to think -- so, yeah, I

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1 have to think about -- I don't know. I don't want to
 2 say anything without thinking about it, but thanks.
 3 I'll think about it.
 4 MR. LEWIS: Eric Lewis at DOJ. So thinking
 5 about Gloria's comments, I think in a model of
 6 collusion, we think about kind of three states of
 7 the -- three possible outcomes, which is either the
 8 baseline or collude or punishment, and so you really
 9 just have those two, either you're cooperating or
 10 you're not, and your control group is sort of nesting
 11 in possible baseline states with also cases where
 12 there might be punishment.
 13 And so I wonder if that is exacerbating the
 14 difference, or I guess the bigger question is, is
 15 thinking about -- you know, given that this is a
 16 repeated interaction, it seems like you could probably
 17 do something a little bit richer to think about how
 18 the outcomes depend not only on what -- just the
 19 communication in the previous period but also what
 20 were the previous periods' outcomes?
 21 MR. ARYAL: So I don't know the answer to the
 22 first one, I have to think about it, but for the
 23 second one, we did -- at one point, we did try to
 24 redefine communication as a continuation, sort of
 25 like, you know, without any break, if everybody's

41	<p>1 serving the market, everybody's talking, and at the</p> <p>2 time we -- the effect was actually much stronger.</p> <p>3 But, again, the difficulty is -- I think the</p> <p>4 difficulty that we had conceptually was to map it to a</p> <p>5 model, and as Gloria said, there isn't any model that</p> <p>6 really fits the market, so we had to make a choice,</p> <p>7 and we decided to just play it safe and say less than</p> <p>8 what we possibly could if we stretched the market a</p> <p>9 little bit. But your point is well taken, yeah. We</p> <p>10 could do something much richer and cut the data in</p> <p>11 many different ways, which we have not done, and I</p> <p>12 think -- but before all of that, before we do all</p> <p>13 that, if we have any energy left, we would probably</p> <p>14 devote it to think about prices. I think that's</p> <p>15 probably more important than anything else, and we</p> <p>16 haven't done that. We don't know how to do it, to be</p> <p>17 honest.</p> <p>18 MR. SINGER: David Singer, Northwestern.</p> <p>19 I could imagine -- sorry. I could imagine a</p> <p>20 model where, let's say, demand is really price in a</p> <p>21 market, is really price-inelastic, and the firms are</p> <p>22 up against their capacity constraints, and just a</p> <p>23 little bit of cut-back in capacity would be really</p> <p>24 good for each firm, and that the cutting back capacity</p> <p>25 really could be a noncooperative equilibrium as</p>	43	<p>1 PAPER SESSION:</p> <p>2 ONLINE PRIVACY AND INFORMATION</p> <p>3 DISCLOSURE BY CONSUMERS</p> <p>4 - - - - -</p> <p>5 MS. CARLSON: Our next paper will be presented</p> <p>6 by Shota Ichihashi from Bank of Canada. He will be</p> <p>7 presenting Online Privacy and Information Disclosure</p> <p>8 by Consumers.</p> <p>9 MR. ICHIHASHI: Thank you very much for having</p> <p>10 me in this great conference. About myself, I am Shota</p> <p>11 Ichihashi. I finished Ph.D. this summer, and I am</p> <p>12 doing microeconomic theory in the Bank of Canada.</p> <p>13 Today I'm talking about online privacy and information</p> <p>14 disclosure by consumers, where I asked the following</p> <p>15 question:</p> <p>16 What are the welfare and price implications of</p> <p>17 a consumer's privacy in online marketplaces? There</p> <p>18 are many ways to tackle this question, but the</p> <p>19 following is what this paper cares about.</p> <p>20 There are online sellers who observe detailed</p> <p>21 information about consumers, say browsing, purchases,</p> <p>22 or their characteristics, but consumers can</p> <p>23 potentially affect to what extent this information is</p> <p>24 revealed. For example, they may delete cookies to</p> <p>25 hide their web browsing activities, or if they are</p>
42	<p>1 opposed to a collusive equilibrium.</p> <p>2 So I'm wondering, is there any way in your data</p> <p>3 that you could begin to get at when -- begin to get at</p> <p>4 the idea that the cut-back could only arise out of</p> <p>5 collusion versus, you know, as just part of a Nash</p> <p>6 equilibrium in capacities noncooperatively.</p> <p>7 MR. ARYAL: Great question. We did try to look</p> <p>8 at how these estimates change when we -- separate</p> <p>9 markets by business passengers, with the idea that</p> <p>10 business passengers have lower elasticity, and so if</p> <p>11 your market has a higher fraction of business</p> <p>12 travelers, then things would -- and -- but we did not</p> <p>13 really use that to think about that the reduction in</p> <p>14 capacity could arise only out of collusion. We did</p> <p>15 not -- we did not really -- but that's a good -- a</p> <p>16 really good point. So we should. We should.</p> <p>17 MS. CARLSON: Okay, I think we are out of time</p> <p>18 (off mic). Thank you.</p> <p>19 (Applause.)</p> <p>20 MS. CARLSON: Great. That was an excellent</p> <p>21 discussion.</p> <p>22 (End of session.)</p> <p>23</p> <p>24</p> <p>25</p>	44	<p>1 more sophisticated, they might create multiple</p> <p>2 accounts on shopping websites to obfuscate their</p> <p>3 purchasing behavior.</p> <p>4 So what I want to capture is the interaction</p> <p>5 between the consumer's incentive to reveal information</p> <p>6 and the seller's incentive regarding how to use the</p> <p>7 information, and to that end, I consider a simple</p> <p>8 model. So this is a theory paper, a simple model,</p> <p>9 where a consumer discloses information to a seller who</p> <p>10 uses the information to make a product recommendation.</p> <p>11 Now, what's that tradeoff? So there are many</p> <p>12 reasons that consumers may or may not want to reveal</p> <p>13 information. There can be some intrinsic privacy</p> <p>14 concern, but this is not what this paper is about. So</p> <p>15 what I study in this paper is the following economic</p> <p>16 tradeoff.</p> <p>17 The benefit for the consumer, the benefit of</p> <p>18 disclosing information is that the seller can learn</p> <p>19 about their preferences and recommend or advertise</p> <p>20 more appropriate products, and the downside is, as you</p> <p>21 might expect, is a potential price discrimination.</p> <p>22 Sellers may base prices on what they learn about</p> <p>23 consumers who capture more of the surplus. And I will</p> <p>24 show how this tradeoff shapes the consumer's incentive</p> <p>25 to reveal information and the seller's incentive</p>

45	<p>1 regarding how to use it.</p> <p>2 Now, I don't have much time to cover the</p> <p>3 detailed literature, but let me just say this is the</p> <p>4 intersection of the theory literature, information</p> <p>5 design, down right, and the literature of the</p> <p>6 economics of privacy, the rest of that box. But I'm</p> <p>7 happy to talk about the marginal contribution offline.</p> <p>8 So it's a theory paper, so I will show you a</p> <p>9 model, and I show many results, and this is the first</p> <p>10 half of the paper. Later, if time allows, I'll</p> <p>11 consider -- I'll talk a bit about the second half of</p> <p>12 the paper as an extension.</p> <p>13 So let's begin with the baseline model, which</p> <p>14 is quite simple. There is a single seller and a</p> <p>15 single consumer, but the seller sells two products,</p> <p>16 product one and two, and the consumer eventually buys</p> <p>17 one of the two products or nothing. And u_1 and u_2 are</p> <p>18 the consumer's variations for products one and two,</p> <p>19 and they are IID, nonnegative and nondegenerate, and</p> <p>20 there is no production cost.</p> <p>21 Preference is standard if consumer buys product</p> <p>22 k, his payoff is value minus price. If he buys</p> <p>23 nothing, he gets an outside option of zero payoff.</p> <p>24 The seller's payoff is its revenue, and both of them,</p> <p>25 both players, are risk-neutral.</p>	47	<p>1 in the model, the math is a bit broken, but before</p> <p>2 observing the product in u_1 and u_2, the consumer</p> <p>3 chooses a disclosure level, which is number δ</p> <p>4 between half and one, and then after this choice, the</p> <p>5 seller observes δ and a signal realization.</p> <p>6 Signal realization is a random variable whose</p> <p>7 distribution depends on which product is more variable</p> <p>8 to the consumer and this δ itself. So, namely, if</p> <p>9 this diagram is correct, whenever product one has a</p> <p>10 higher value with probability δ, signal one is</p> <p>11 realized. Whenever product two has a higher value</p> <p>12 with probability δ, signal two is realized.</p> <p>13 So one important observation is that the</p> <p>14 greater disclosure level δ the consumer chooses,</p> <p>15 the more accurately the seller can learn about which</p> <p>16 product is likely to be the best. So intuitively --</p> <p>17 so δ is a precision. δ is how much personal</p> <p>18 data the consumer discloses, and implicit assumption</p> <p>19 is that if the consumer disclose more, the seller can</p> <p>20 learn more about which product is more likely to be</p> <p>21 suitable to the consumer.</p> <p>22 So what's the interpretation of signal one and</p> <p>23 signal two? So signal one and two indicates the</p> <p>24 consumer is more likely to love one product than the</p> <p>25 other, and how this particular signal looks like</p>
46	<p>1 Now, so, this is the primitive of the model.</p> <p>2 Now, let's see the timeline of the game. So I will</p> <p>3 show timeline, but what I want you to remember from</p> <p>4 this slide is I consider two models, two different</p> <p>5 games, that differ in whether the firm can</p> <p>6 price-discriminate.</p> <p>7 In one model, a model of nondiscriminative</p> <p>8 pricing, the seller sets a price for each product at</p> <p>9 the very beginning. And then taking prices as given,</p> <p>10 the consumer discloses information. The seller learns</p> <p>11 something about his preferences, and then the seller</p> <p>12 makes product recommendation. Consumer makes a</p> <p>13 purchasing decision, and the game ends.</p> <p>14 The other model is a model of discriminatory</p> <p>15 pricing. The only difference is that the consumer</p> <p>16 discloses information and then the seller sets prices.</p> <p>17 So we consider two models that differ in the timing at</p> <p>18 which the seller sets the prices.</p> <p>19 Now, if this is clear, let me talk about three</p> <p>20 components which are common between the two pricing</p> <p>21 regimes; namely, disclosure, recommendation, and</p> <p>22 purchasing decision. So let me begin with the</p> <p>23 consumer's information disclosure.</p> <p>24 So this slide summarizes information disclosure</p> <p>25 and is probably most important slide in the setup. So</p>	48	<p>1 highly depends on the particular application. I don't</p> <p>2 cover the application in this talk, but basically this</p> <p>3 diagram summarizes a situation in which the consumer</p> <p>4 can affect how precisely the seller can learn about</p> <p>5 his preferences.</p> <p>6 And, again, let me just emphasize, when the</p> <p>7 consumer chooses δ, he doesn't know his</p> <p>8 valuations, so we don't need to worry about cheap-talk</p> <p>9 problem or we don't need to worry about the</p> <p>10 possibility that consumer manipulates signal one and</p> <p>11 two ex post.</p> <p>12 All right. So this is information disclosure.</p> <p>13 Consumer chooses Δ. Seller learns which product</p> <p>14 is more likely to be best with a different precision.</p> <p>15 And then, after that, again, regardless of the pricing</p> <p>16 regime, the seller updates his belief and recommends</p> <p>17 one product, and the consumer sees the varying price</p> <p>18 of the recommended product, and he decides whether or</p> <p>19 not to purchase the recommended product.</p> <p>20 Recommendation can lead to relatively which</p> <p>21 product to recommend, or depending on application, it</p> <p>22 can be which online ad to display, as I discuss in the</p> <p>23 paper, but in terms of the formulation, what's</p> <p>24 important here is that while the seller sells two</p> <p>25 products, it can only recommend one product, and the</p>

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1 consumer can -- a consumer decides whether to buy the
2 recommended product -- namely, he cannot purchase the
3 product that is not recommended -- and so this is not
4 the result of seller's optimization, of course. This
5 is an assumption.

6 With this assumption, consumer can only
7 evaluate the one product, and what this tries to
8 capture is the situation where the consumer's
9 attention is limited; namely, compared to the variety
10 of the whole products, here two, the consumer can
11 evaluate only a small subset of the products, here
12 only one. This particular formulation of limited
13 attention is in line with the -- some theory --
14 decision theory approach of limited attention. One
15 twist here is that it is the seller who affects what
16 products the consumer pays attention to.

17 All right. So this is basically the whole
18 timing of the game. So let me just wrap up the setup.
19 Under nondiscriminatory pricing, pricing comes first,
20 product one and two, and then consumer reviews the
21 information delta. Then seller learns about which
22 product is more likely to have a higher value, so
23 recommends product. Consumer sees the value and
24 decides whether or not to buy.

25 Under discriminatory pricing, after information

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1 disclosure, the seller decides which product to
2 recommend with what price, and I consider a subgame
3 profit equilibrium with some tie-breaking rule. Now,
4 if this is clear, let me move on to solving the model.

5 So I will solve the game backward. So I will
6 show that how recommendation and pricing look like,
7 and then I will show the entire equilibrium. This
8 slide summarizes the seller's equilibrium
9 recommendation strategy, which is quite intuitive.

10 For example, given any delta, signal two suggests the
11 consumer is more likely to have a higher value for
12 product two. So regardless of which pricing regime we
13 focus on, the seller optimally recommends product two.

14 And from the consumer's perspective, this means
15 the benefit of more information disclosure. The
16 higher delta disclosure level implies he's more likely
17 to be recommended the best product. If the delta is
18 one, he surely recommended whichever product has a
19 higher value.

20 The question is, how does this more disclosure
21 and better recommendation affect product prices, which
22 is -- to the consumer, this is relevant under
23 discriminatory pricing. So suppose the consumer
24 increases delta from some number above half, which
25 means the seller is more likely to recommend the best

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1 product, the product with the higher value. The value
2 is maximum of u_1 and u_2 , and how does this affect the
3 consumer's value distribution for the recommended
4 product, and how does this affect the pricing?

5 Now, I don't show the math, but basically if
6 the consumer discloses more information and if the
7 seller is more likely to recommend the best product,
8 consumer's value distribution for the recommended
9 product has a lower hazard rate just using the
10 property of the higher and lowered ordered statistics
11 of two random variables, and this intuitively captures
12 the idea that the consumer's demand for the
13 recommended product becomes less elastic. Therefore,
14 the seller, monopolistic seller, charges a higher
15 price.

16 So what happens in this model under
17 discriminatory pricing is that if the consumer
18 discloses more information, then recommendation gets
19 better, which in turn implies the consumer demand
20 becomes less elastic, which gives the seller an
21 incentive to raise a high price.

22 Now, so, what we've seen is more information
23 disclosure leads to the higher price -- no, more
24 information disclosure leads to better recommendation
25 first, but under discriminatory pricing, it leads to

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1 the higher price, and by combining these observations,
2 we get the first result. Each pricing regime has a
3 unique equilibrium, which I show in the paper, and the
4 seller is better off and the consumer is worse off
5 under nondiscriminatory pricing.

6 In other words, the seller prefers to commit
7 not to price-discriminate, which makes the consumer
8 worse off. This is a little bit different from what
9 we might imagine it from the standard price
10 discrimination model, so let me give intuition.

11 So as we saw before, under nondiscriminatory
12 pricing, a consumer chooses a disclosure level, taking
13 prices as given. So what he cares about is just a
14 recommendation accuracy. So it is optimal for the
15 consumer to set the highest disclosure level to make
16 sure that he's recommended the best product.

17 However, when the seller sets a price for each
18 product up front, the thing is like this. When the
19 seller considers what price to set product one,
20 because the seller knows consumer is going to disclose
21 much information with which the seller can make
22 accurate recommendation, so that this product one is
23 going to be recommended only to consumers who have
24 high valuation for it. So, therefore, the seller sets
25 a relatively high price for each product, one and two,

53	<p>1 in advance.</p> <p>2 Now, in contrast, when the consumer discloses</p> <p>3 the information first under discriminatory pricing,</p> <p>4 the consumer is in some sense the first mover</p> <p>5 (indiscernible) leader, who can chose a disclosure</p> <p>6 level, balancing the benefit from better</p> <p>7 recommendation and a cost from a higher price. As a</p> <p>8 result, he chooses a weakly lower disclosure level by</p> <p>9 which he can enjoy a weakly lower price and a higher</p> <p>10 payoff, although recommendation can be a bit noisier.</p> <p>11 So what happens is the seller wants to commit</p> <p>12 to nondiscriminatory pricing, which encourages</p> <p>13 information disclosure, but in this pricing regime,</p> <p>14 consumers disclosing too much information in the sense</p> <p>15 that if the consumer could precommit to withhold some</p> <p>16 information, he could be better off.</p> <p>17 Now, this intuition is based on the relative</p> <p>18 commitment power or the timing of moves between the</p> <p>19 seller and the consumer, but today I'd like to show</p> <p>20 that another intuition, which is based on the</p> <p>21 following alternative interpretation of the model. So</p> <p>22 only in this slide let's forget about the single</p> <p>23 consumer model, but imagine there are a unit mass</p> <p>24 continuum of consumers, and in this interpretation, in</p> <p>25 this formulation, under discriminatory pricing, the</p>	55	<p>1 to a larger fraction of consumers, but these higher</p> <p>2 prices lower the welfare of other 900 consumers who</p> <p>3 might not decide to disclose information. So what</p> <p>4 happens here is information disclosure by consumers</p> <p>5 lower the welfare of other consumers through higher</p> <p>6 prices when the seller cannot personalize prices. So</p> <p>7 in equilibrium, consumers disclose more information</p> <p>8 than what would maximize the joint surplus.</p> <p>9 So in contrast, if the seller can personalize</p> <p>10 prices, each consumer take into account the impact of</p> <p>11 his disclosure on prices, so in total, consumers</p> <p>12 disclose weekly less information, and they are</p> <p>13 collectively better off. So this is a bit outside</p> <p>14 based on the alternative formulation. So let's get</p> <p>15 back to the original single consumer model, and this</p> <p>16 is the same slide as the previous, previous slide. So</p> <p>17 let me give you two relatively straightforward</p> <p>18 implications of this result.</p> <p>19 So, one, this gives a seller a rationale for</p> <p>20 committing not to price-discriminate. Of course,</p> <p>21 there can be many, but one story is that once the</p> <p>22 seller starts to price-discriminate, consumers are</p> <p>23 discouraged from providing information, and this</p> <p>24 lowers the matched quality between the products and</p> <p>25 the consumers and hurts revenue.</p>
54	<p>1 seller can charge different prices to different</p> <p>2 consumers, and, of course, recommend different</p> <p>3 products to different consumers.</p> <p>4 Now, under this nondiscriminatory pricing,</p> <p>5 still the consumer disclose information first. Many</p> <p>6 consumers disclose information, and then the seller</p> <p>7 sets a single price for each product and then make</p> <p>8 recommendation. So there is a slight difference.</p> <p>9 There are many consumers, and difference of pricing</p> <p>10 regime is whether the seller can personalize prices.</p> <p>11 In the paper, I argue this is essentially the</p> <p>12 same as the original model we've seen, and, in</p> <p>13 particular, consumers are worse off under</p> <p>14 nondiscriminatory pricing, but in the current</p> <p>15 alternative interpretation, we can think of this as a</p> <p>16 classic tragedy of the commons due to the following</p> <p>17 negative externality associated with information-</p> <p>18 sharing. So here's what I mean by negative</p> <p>19 externality.</p> <p>20 So suppose there are 1000 consumers,</p> <p>21 nondiscriminatory pricing, and suppose there's 100</p> <p>22 consumers disclose more information. This gives the</p> <p>23 seller an incentive to charge a higher price for each</p> <p>24 product because, on average, the seller can recommend</p> <p>25 the better product, can give a better recommendation</p>	56	<p>1 As this intuition suggests, it is really</p> <p>2 important that there are multiple products, important</p> <p>3 that the consumer cannot evaluate all products, and</p> <p>4 also important that consumer can affect how much</p> <p>5 information to disclose. So this highlights the key</p> <p>6 variable here is the fact that consumer can affect how</p> <p>7 precisely the seller can learn about themselves, learn</p> <p>8 about consumers' preferences.</p> <p>9 The second is a little bit on policy side, so I</p> <p>10 don't have a specific regulation in mind, but the</p> <p>11 observation that consumers disclose more information</p> <p>12 than what would maximize their joint surplus suggests</p> <p>13 there might be some regulation which limits the</p> <p>14 consumers' disclosure or the regulation which limits</p> <p>15 the amount of information that sellers can seek for</p> <p>16 which benefits consumers. So this is because such a</p> <p>17 regulation might restore the consumer's commitment</p> <p>18 power to withhold information from sellers. Now, so,</p> <p>19 these are the two implications, and we cover the first</p> <p>20 half of the paper.</p> <p>21 Now, let me spend the rest of the time to talk</p> <p>22 about the second half of the paper, which -- where I</p> <p>23 study the following unrestricted model, which is the</p> <p>24 unrestricted version of the model. So, first, the</p> <p>25 seller doesn't just sell two products. Seller can</p>

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1 sell K products with IID values, and more importantly,
2 the consumer can disclose any information about this K
3 dimension random variable or vector. So I don't show
4 you a formulation of what I mean by "any information,"
5 but in this model, the consumer can, for example,
6 disclose the name of the -- consumer can let the
7 seller learn which product has the lowest value, or
8 the consumer can let the seller learn his willingness
9 to pay for a particular subset of the products. So
10 the consumer's choice set about disclosure is
11 extremely rich.

12 Now, why do I consider such a situation?
13 Absolutely not because I think this is the most
14 realistic, but because I want to see, one, robustness
15 check of the main finding with respect to the
16 assumption of what information the consumer can
17 disclose. Here, consumer doesn't just disclose the
18 information of which product is better, but he can
19 potentially let the seller learn his vertical
20 willingness to pay.

21 And another important reason is that this
22 connects the paper to the theory literature. In
23 particular, the recent AER paper by Bergemann and
24 Brooks and Morris, 2015, which is basically the -- so
25 my single product version model, this model, feeds

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1 their work.

2 Unfortunately, I don't have time to analyze the
3 model, but the punchline is we get the same result.
4 Whenever product two -- no, whenever the seller sells
5 multiple products, the seller is, again, better off
6 and the consumer is worse off under nondiscriminatory
7 pricing, and also under a very mild assumption on the
8 distribution -- the variation distribution, we can
9 conclude seller is strictly better off and a consumer
10 is strictly worse off under nondiscriminatory pricing.

11 So the proof is much, much longer, but
12 basically I show that nondiscriminatory pricing, as we
13 can expect, it has a benefit of encouraging disclosure
14 which leads to better recommendation, but to the
15 seller, there is an obvious loss, which is the seller
16 cannot tailor prices on information. So what proof
17 shows is the benefit dominates a loss from the
18 seller's perspective.

19 But actually, in the paper, I can never derive
20 the -- what information the consumer reveal under
21 discriminatory pricing, so without knowing the
22 disclosure policy, I compare the seller and the
23 consumer welfare, and in the middle step, I
24 characterize the most efficient disclosure policy of
25 the consumer.

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1 And the result theorem is in contrast to the
2 Bergemann, Brooks, and Morris, in the sense that -- in
3 the sense that in this result, the seller has a strong
4 preference toward nondiscriminatory pricing, under a
5 mild condition, but in the single product version, the
6 seller is indifferent between two pricing regimes,
7 which I think itself is interesting.

8 Now, so, the -- what's left, I haven't talked
9 about the sum of consumer and the seller total
10 welfare. One natural question is can
11 nondiscriminatory pricing, which the seller prefers,
12 enhance total surplus? The answer is no if there is
13 only one product. The answer is it depends if there
14 are multiple products.

15 In our paper, I formally show nondiscriminatory
16 pricing always leads to the more efficient
17 recommendation, never -- there is never product
18 match -- product mismatch under discriminatory
19 pricing. It always leads to the highest probability
20 of a trade. So it depends on which effect dominates,
21 which pricing regime is more efficient. If there are
22 many products, then the first effect dominates. If
23 there are many products with IID values, eventually
24 nondiscriminatory pricing leads to a greater total
25 surplus because it encourages disclosure and leads to

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1 better recommendation.

2 All right. I have more than one minute, so let
3 me cover. So another question of our thinking is can
4 there be some institution which can improve the total
5 welfare farther, and one thing we often talk about is
6 when it comes to personal data, the rough idea is if
7 there is a market for data, it can enhance the
8 welfare. There is a -- this is a naive way of
9 incorporating market for data in my model.

10 So basically, in addition to the model, I
11 explained at the very beginning the seller can offer
12 the consumer to purchase information and make a -- pay
13 money. What I show is that under nondiscriminatory
14 pricing, this additional stage of buying data has no
15 impacts, because consumer's happy to disclose
16 information for free.

17 Under discriminatory pricing, this additional
18 stage of asking information and pay money can improve
19 the seller's revenue without affecting -- without
20 lowering consumer's payoff. So in this case, seller
21 asks the consumer to reveal full information and to
22 make a transfer, which keeps the consumer just
23 indifferent between accepting and rejecting the offer,
24 and as a result, there is a perfect price
25 discrimination, which is efficient.

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1 Now, let me wrap up. So the question I'm
 2 interested in is what are the welfare and price
 3 implications of consumers' privacy, and the
 4 conclusion, under some assumptions, seller is willing
 5 to commit not to price-discriminate, which hurts the
 6 consumer but may improve total welfare. Thank you so
 7 much.
 8 (Applause.)
 9 MS. CARLSON: Thank you.
 10 Next we will have Guy Arie from the University
 11 of Rochester, Simon School, to give a discussion.
 12 MR. ARIE: All right. Yeah, so thank you for
 13 the organizers. It's a wonderful conference. And
 14 thanks, David, for inviting me. And, Shota, it's a
 15 very interesting paper.
 16 So very quickly, so what is this paper about,
 17 right? It's how do sellers use the buyer's
 18 information. And let me try to, like, give -- we're
 19 going to get to an example, but basically there's two
 20 things that he's trying to talk about. One is sellers
 21 can use the information to just offer you a better
 22 matching product, okay? And the second is they can
 23 use the information to price-discriminate.
 24 And the point -- right, so, for example, I need
 25 to -- I get to decide what Amazon sees, like what I --

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1 which news I see and whatever -- you know, Amazon
 2 knows a lot about me, and they can use that to decide
 3 which Halloween costumes to suggest to me, right, or
 4 they can use that to decide also how much to price the
 5 various Halloween costumes that they suggest to me,
 6 right? And so that's the two dimensions that he's
 7 going to talk about.
 8 And the main point of the paper is I'd actually
 9 benefit not only from letting -- so we're not going to
 10 talk about do I benefit exactly from letting Amazon
 11 know everything about me, but in the world that Amazon
 12 knows enough about me, I actually benefit from them
 13 price-discriminating. So let's see how, and you can
 14 only see the -- something that someone like that --
 15 it's about that.
 16 So not going into the model components too
 17 much, just think about it -- you know, the way you
 18 really want to think about it is there's a monopolist,
 19 let's say that's me, and I am selling you two
 20 products, okay? Now, these two products have downward
 21 sloping demand curves, but it happens to be that half
 22 of you like this product more than you like that
 23 product, all right? So there's two downward sloping
 24 demand curves.
 25 For half of the population, this one is higher.

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1 For half of the population, this one is a little bit
 2 higher. The problem is, I don't know which one, okay?
 3 So that's how I start -- that's how we start this
 4 model. I don't know which one, okay?
 5 So what happens if I don't know anything, okay?
 6 The problem is you can't go to the one you like more.
 7 That's the problem this monopolist is facing. You
 8 have to go to someone you don't know which product you
 9 like more, and I don't know which one to offer you, so
 10 I just basically can -- because IID, but I might as
 11 well sell everyone this one, okay, because I don't
 12 know, and as a result, my demand curve isn't that
 13 great, okay, because it's coming from the aggregate
 14 population.
 15 So what happens if I know, okay, so full
 16 disclosure without price discrimination, so that's the
 17 first thing -- that's basically the baseline for this
 18 model, all right? So what he's saying is, okay, now
 19 what's going to happen is relative to the world that I
 20 don't know, so I'm facing -- as a monopolist, I'm
 21 facing this one downward sloping demand curve. And
 22 now I actually am going to know, so you're going to
 23 come, and I'm going to tell you you go right, and
 24 you're going to come, and I'm going to tell you you go
 25 left, okay, and actually have information to base that

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1 on, okay?
 2 So if I have information to base that
 3 recommendation on, what's going to happen is I can
 4 say, you know what, I have a -- I'm a monopolist. I
 5 have a downward sloping demand curve for this product.
 6 I have a downward sloping demand curve for that
 7 product. I'm just going to price it accordingly, you
 8 know, I don't care about the -- you guys not knowing,
 9 because you are going to know, okay? So that's the
 10 first result that we have, okay?
 11 As a result of this, as a monopolist, I am
 12 doing better, right? The demand curve is higher, so I
 13 am getting more revenue, and, in fact, in this model,
 14 in this paper, I am going to get the best -- the
 15 highest revenue that I can as a monopolist, okay?
 16 So if we think about this, there's two forms of
 17 price discrimination that are going to come in. Here,
 18 the price discrimination is completely independent
 19 both of the fact that -- how honest you chose to be
 20 with me as the monopolist and what you actually told
 21 me, okay?
 22 In practice -- and I could, you know, price-
 23 discriminate based only on how honest you choose to be
 24 with me, and I can also choose to price-discriminate
 25 based on what exactly you told me. Because I don't

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1 discriminate on anything, I have two products, it ends
2 up being in your best interest as a buyer to just tell
3 me the best thing, because I'm just going to tell you
4 where to go, okay? So all this centers on the line,
5 and I am just going to be a very profitable monopoly,
6 all right?

7 Notice that we don't need to have any
8 information disclosure, right? What we could have is
9 just there's a product here, there's a product there,
10 they have prices. You, customers, go choose whichever
11 one you like, okay? I am going to set the same
12 prices, okay? So, like, fixing a problem here by full
13 disclosure that we don't necessarily have to have if
14 we don't have -- if we have enough information, and,
15 of course there could be reasons that we don't have
16 the information.

17 Another observation about this is we tend to
18 assume, you know, before we start thinking about value
19 rationality very carefully and all of that, we
20 generally tended to assume that the customers are
21 pretty well informed, right? So well informed
22 customers tended to be the best, and here it's
23 actually the worst case scenario in a sense. Other
24 observations are less important for this discussion.

25 So this is the baseline, and now we can talk

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1 about price discrimination, all right? So, in fact, I
2 can price-discriminate, like I said, based on two
3 things, how honest you are with me, so do you let me
4 see everything you do, okay, at home? Do you have an
5 Alexa, right? Or what exactly did you tell me, right?
6 Did you tell Alexa that you really like wearing very
7 scary costumes? So two different things that I can
8 price-discriminate based on.

9 So if I only discriminate on policy, okay,
10 what's going to happen? Well, you already know as
11 customers that if I only discriminate -- if I don't
12 discriminate -- if I don't discriminate at all, okay,
13 then I'm basically going to act like a very, you know,
14 vicious monopolist, right? So it's actually in your
15 best interest to make me be scared a little bit, okay,
16 to make me less certain as a monopolist.

17 So if I only disclose based on policy, some of
18 you are going to have Alexa and some of you are not
19 going to have Alexa, right, and I'm not going to know
20 which is which. I only know how many Alexas there are
21 in the world, and that's going to make me, as a
22 monopolist, a little bit softer, because I need to
23 handle the fact that some people are going to the
24 wrong product, right, and that's going to actually
25 decrease the price, okay.

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1 So that's basically what happens if I only
2 discriminate based on price, right, or that's the
3 intuition. Then, if I discriminate -- what happens if
4 I discriminate based on price? Well, if I
5 discriminate based on price, given that I'm pricing as
6 a monopoly already, okay, it ends up that you as
7 buyers could do a little bit better, because you're
8 not going to tell me, hey, price even higher, right?
9 You are not going to give me -- as long as you have
10 control for what you are disclosing, you are not going
11 to disclose information that tells me to price even
12 higher, but because you have control over what you're
13 disclosing, maybe you could figure out a way to tell
14 me, you know what, price a little bit lower for me,
15 okay? Not for everyone, but for me, price a little
16 bit lower, okay?

17 If you can commit initially to do that in a
18 credible way, I'm going to go along with it, right?
19 And that's the second main result of this paper, is
20 that if there is full information disclosure, so if
21 you have complete flexibility in how much information
22 you disclose as buyers, then you are actually going to
23 use that, if you could, to give me exactly the right
24 information to make sure that no one goes away
25 empty-handed, okay? As a monopolist, I am going to

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1 actually give everyone discounts, that if I can't --
2 if I need to, to make sure that everyone buys
3 something.

4 So now that we understand -- so, like, this is
5 what's going on, what can we say about this? Well,
6 this works because you, the buyers, have a whole lot
7 of control here, right? You, the buyers -- it's not
8 like you tell me, hey, here's everything about me.
9 Alexa is in my house. You know everything about me,
10 right? No, that's not full disclosure, right? Full
11 disclosure here is here is exactly the right things I
12 want Alexa -- like, I'm committing ahead of time.
13 This is -- and I'm fooling Alexa, right, but I'm
14 committing ahead of time to when exactly is Alexa
15 going to hear things in my kitchen, okay?

16 And when I commit exactly, then it's only, you
17 know, when my kids cry and I say, "You are not going
18 to get a Halloween costume," and if they hear that
19 enough, maybe they're going to give me a discount,
20 okay? So in that world, okay, I can get some
21 information disclosure in letting Amazon
22 price-discriminate based on the information that they
23 hear from me actually works, because I'm giving out
24 the signals that say, hey, Amazon, I deserve a
25 discount, okay?

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1 But in the world where full disclosure is --
 2 where Alexa hears everything, we might actually be
 3 closer to, you know, the firm knows exactly how
 4 much -- Amazon knows exactly how much I'm going to pay
 5 for a costume, and they are going to tell me the only
 6 costumes we have left are like, you know, 35 bucks.
 7 So what's going to happen? We're going to have
 8 increased efficiency, because Amazon is going to know
 9 exactly, for every one of us, how much we are willing
 10 to pay. So everyone is going to buy, okay? But, of
 11 course, you know, not a whole lot of surplus for
 12 consumers.

13 So the policy relevance, there's a lot of
 14 policy -- you know, there's a lot of things. The main
 15 thing I want to -- you know, in terms of, you know,
 16 FTC, competition, right? There's this Corts paper
 17 that I really like. Take all of this, throw
 18 competition in it, a lot of problems get solved, and
 19 even are better for customers, all right? So a lot of
 20 the results here are coming from the fact that we're
 21 starting from a monopolist. A lot of other policy
 22 things that we're going to skip because I wanted to
 23 really get across the intuition of the paper.

24 It's a really interesting paper of sales
 25 accounts. Really, it's a terrific piece of research

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1 on really a difficult and important question. We need
 2 to think about this more, mainly on can we have models
 3 where the baseline model isn't this dystopian
 4 monopoly, all right? If we can stop for someone
 5 there, then we can see what happens with
 6 discrimination and so on, right?

7 That's it. Thank you very much. Great paper.
 8 (Applause.)

9 MS. CARLSON: All right. So, I'll ask Shota to
 10 come back up, and we'll open the floor for questions.

11 AUDIENCE MEMBER: Yeah, we're just wondering if
 12 you can actually highlight the difference between your
 13 paper and the Roesler and Szentes papers in which the
 14 buyers can actually learn about the evaluations, or in
 15 this way I'm thinking that the signal structures that
 16 the consumers are committing themselves to is the same
 17 as, you know, learning about their own evaluation,
 18 since they don't know it anyways.

19 MR. ICHIHASHI: So that's the Buyer Optimal
 20 Learning paper.

21 AUDIENCE MEMBER: Yeah. Yeah, that one.

22 MR. ICHIHASHI: Yeah. So I think one way to
 23 think of this model can be a multiproduct version of
 24 their model. So in my model, the way in which
 25 consumer gets to the best product is to let the seller

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1 learn about consumer's preferences, and as a revenue-
 2 maximizing seller, it recommends the best product.

3 And I naively extend their work, buyer
 4 learning, to multiproduct, I can imagine a situation
 5 where I commit to what I learn about the values of the
 6 two products, and based on the information, I go to
 7 whichever product gives me a higher profit. But like
 8 I said, if we think of the two products, multi version
 9 of the paper Buyer Learning, there may be a similar
 10 force in the sense that buyer wants to commit to learn
 11 less about the variations of the products by which he
 12 gets a noisier product match, but monopolist sets a
 13 lower price. Yeah.

14 AUDIENCE MEMBER: Yeah.

15 AUDIENCE MEMBER: So I'm wondering, so, for
 16 example, for the discussion -- the example was Amazon,
 17 and so Amazon is a platform that sells products that
 18 are made by other, let's say, manufacturers. So in
 19 that case, how would the model change once you take
 20 into account that the products themselves are actually
 21 produced by different manufacturers and they actually
 22 compete -- I guess what I'm trying to ask as well is
 23 that, how will I learn the incentives of the upstream
 24 in the platforms?

25 MR. ICHIHASHI: I see. I see. Yeah, that's

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1 one reason I cannot say that math model exactly fits
 2 Amazon, in the sense that there are other sellers
 3 providing the same product. And, yeah, I don't have
 4 an exact answer. The main reason is that -- so in my
 5 model, a consumer can examine only one product, but to
 6 take into account the existence of multiple sellers,
 7 we have to consider not only the competition, but also
 8 we have to alter the assumption of how many products
 9 the consumer can examine.

10 So if multiproducts that I can consider an
 11 extension where there are multiple sellers, there are
 12 k sellers, they make recommendation, and I can
 13 randomly pick two, not just one, and take the
 14 whichever better for me, and that kind of competition
 15 can actually turn over the -- my main result
 16 monopolist, but I think taking into account that there
 17 are other sellers in Amazon providing the similar or
 18 same product, I don't have a good idea formulating,
 19 mainly because I don't know how to think of the
 20 consumers' reconciled limited attention with existence
 21 of multiple sellers.

22 MS. JIN: So I have -- I'm wondering how your
 23 model changes with dynamics. We know many sellers
 24 keep the data in their house for very long time, and
 25 if -- I'm reluctant to talk about costume -- Halloween

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1 costume this year, but they can use my talk last year
2 or my purchase last year to inform my preference. On
3 the other hand, you could also have consumers learning
4 the quality of the seller recommendation over time.

5 MR. ICHIHASHI: Yeah. So I think the multiple
6 product with dynamic pricing, so dynamic pricing and
7 the temporal pricing, intratemporal pricing of its
8 consumers is an interesting extension, and I can
9 imagine if the consumer can take into account the
10 impact of today's disclosure in the old future, then I
11 think that -- I believe the similar economic force
12 should arise, namely, consumer can -- are discouraged
13 from providing information if they know information is
14 going to be used in the future.

15 But I think that another topic I'm interested
16 in is consumer typically know in the very long future,
17 he doesn't know how the information will be used, so
18 once we incorporate something like the time
19 inconsistency or the fact that I don't know in the
20 future how my information will be used, then, you
21 know, there may be something interesting, but that's
22 the case, yeah. I don't know, and I'm interested in
23 it.

24 AUDIENCE MEMBER: And so my question is also
25 related to Ginger's question. So here you're assuming

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1 that consumers control exactly what information is
2 given by the firm, and then in the next round, you're
3 assuming that consumers are not attentive and they
4 can't go and see other products, when in the first
5 round you were sort of assuming they know exactly
6 their value for all the products. How do you
7 counterbalance those assumptions?

8 MR. ICHIHASHI: Yeah, and that's a very good
9 question. So one is limited attention for product
10 search, and the other is, in some sense, inattention,
11 so a limited attention product search and have
12 attention to control the information. So I think
13 the -- like website like Amazon, putting aside whether
14 it's monopolist, say Amazon, eBay, it's the
15 institutional feature of the websites to show only a
16 subset of the products. I mean, they can never move
17 to a situation where they have alphabetical listing of
18 all the products.

19 So in that case, no matter how sophisticated
20 about controlling information, it's impossible for me
21 to exhaustively evaluate all the products. So in that
22 sense, I think the -- being able to figure out how to
23 retrieve information doesn't necessarily contradict
24 not being able to find exact product I want by myself,
25 but that point makes sense.

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1 Another situation I think -- model may fit is
2 offline transaction, like the car dealers, where I
3 give the car dealer, the salesperson, some preference
4 about my car and get some suggestions and do a test
5 drive. So in that situation, I think it's relatively
6 easy to imagine how to conceal some information. I
7 would not want to dress like this, I would wear cheap
8 clothes, or I may be more reluctant to talk about my
9 preference over fuel efficiency and horsepower if I
10 know that price is very flexible based on the
11 customer. But that's a very fair point.

12 MR. BRUESTLE: Hi. Steven Bruestle, Federal
13 Maritime Commission.

14 Sellers often try to induce me to disclose my
15 information by offering me a discount. Have you
16 considered how this would affect your model? Maybe it
17 would be something in between your two cases.

18 MR. ICHIHASHI: So what you mean is that if you
19 provide information, I will give you a discount.

20 MR. BRUESTLE: Right, say 15 percent off -- 5
21 percent off, 10 percent, 15 percent off the final
22 price.

23 MR. ICHIHASHI: Yeah, right. So if the seller
24 can -- so in the model, if the seller can make the
25 price contingent on what the information disclosed,

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1 then as Guy suggested, there is a dystopian situation.
2 I don't know how exactly to incorporate that
3 observation, but the idea that the seller's ability to
4 make transfer contingent on what information
5 disclosure, that's reflected in the market for data
6 part, the very end, in the sense that if the consumer
7 can say no to the transfer and then start to play the
8 original game, he disclose whatever he want, then in
9 equilibrium, the seller makes the transfer, which
10 makes the consumer weakly better off, but consumer is
11 willing to disclose, and the seller can tailor prices.

12 But in that case the consumer get money, happy
13 to disclose information, and then he's price-
14 discriminated on the product. So he may be -- seller
15 may get a high or low price depending on the
16 informational content, so that doesn't exactly fit
17 what you are saying, but, yeah, I'd have to think of
18 how to get a model explaining that observation. But I
19 agree that that's a pretty common phenomenon.

20 MR. BRUESTLE: Okay. Thank you.

21 MR. ICHIHASHI: Yeah.

22 MS. CARLSON: Any other questions?

23 (No response.)

24 Thank you.

25 MR. ICHIHASHI: Thank you.

77	<p>1 (Applause.)</p> <p>2 MS. CARLSON: So we will take a short break for</p> <p>3 coffee and conversation. We will reconvene back here</p> <p>4 at 11:20.</p> <p>5 (End of session.)</p> <p>6</p> <p>7</p> <p>8</p> <p>9</p> <p>10</p> <p>11</p> <p>12</p> <p>13</p> <p>14</p> <p>15</p> <p>16</p> <p>17</p> <p>18</p> <p>19</p> <p>20</p> <p>21</p> <p>22</p> <p>23</p> <p>24</p> <p>25</p>	79	<p>1 published in leading professional journals in</p> <p>2 economics and business, including in Econometrica,</p> <p>3 American Economic Review, Quarterly Journal of</p> <p>4 Economics, and Review of Economic Studies.</p> <p>5 Dr. Besanko is a Northwestern University Kellogg</p> <p>6 graduate, having received his Ph.D. in managerial</p> <p>7 economics and decision sciences in 1981. Please join</p> <p>8 me in welcoming Dr. Besanko.</p> <p>9 (Applause.)</p> <p>10 MR. BESANKO: Thank you, Julie.</p> <p>11 I want to thank the Bureau of Economics for</p> <p>12 asking me to be on the scientific committee. You</p> <p>13 know, what we did, Ali and Katja and I, was really</p> <p>14 kind of the tip of the iceberg to all of the work that</p> <p>15 the economists here in the Bureau did. We each read</p> <p>16 about a dozen papers and, from those, put together the</p> <p>17 program, but before we got to that point, the</p> <p>18 economists here at the Bureau had read, what, over 150</p> <p>19 papers, something like that, and so there's a lot of</p> <p>20 intellectual heft that's behind this conference.</p> <p>21 When I joined the faculty at Kellogg 25 years</p> <p>22 ago, I joined the strategy group, and occasionally</p> <p>23 people would ask me, what is someone who is doing</p> <p>24 economics of regulation doing in a strategy group?</p> <p>25 And I would sometimes say that, well, my goal</p>
78	<p>1 KEYNOTE ADDRESS:</p> <p>2 HOW EFFICIENT IS DYNAMIC COMPETITION?</p> <p>3 THE CASE OF PRICE AS INVESTMENT</p> <p>4 - - - - -</p> <p>5 MR. ROSENBAUM: Hi, everyone. Before I turn it</p> <p>6 over to Julie to introduce our keynote, just two brief</p> <p>7 announcements. One is we have copies of the papers</p> <p>8 that are being presented today on the back table, so</p> <p>9 if people are interested, please feel free to take</p> <p>10 those.</p> <p>11 And the other announcement is, unfortunately,</p> <p>12 we don't have WIFI. It's not working in the building.</p> <p>13 If for some reason you don't have internet and need it</p> <p>14 for some urgent reason, please come talk to me or</p> <p>15 Nathan and we will get you hooked up with something.</p> <p>16 So I'll turn it over to Julie.</p> <p>17 MS. CARLSON: Well, welcome back from the</p> <p>18 break.</p> <p>19 It is my pleasure to introduce our keynote</p> <p>20 speaker. Dr. David Besanko is IBM Professor of</p> <p>21 Regulation and Competitive Practices at the Kellogg</p> <p>22 School of Management at Northwestern University.</p> <p>23 Dr. Besanko's research covers topics relating to</p> <p>24 industry dynamics, industrial organization, and the</p> <p>25 economics of regulation. He has over 50 articles</p>	80	<p>1 eventually is to work on research that's at the</p> <p>2 intersection of competitive strategy and economics and</p> <p>3 regulation. I'm not quite sure that I've ever got</p> <p>4 there, but I do hope that this stream of research that</p> <p>5 I've been doing with Ulrich Doraszelski and Yaroslav</p> <p>6 Kryukov, and in the past with Mark Satterthwaite as</p> <p>7 well, is kind of inching in that direction.</p> <p>8 So today I want to talk about this topic that</p> <p>9 we have been working on for the last eight to ten</p> <p>10 years, which is trying to understand markets where</p> <p>11 price serves as an investment, and, in particular, for</p> <p>12 the paper that I'm going to talk about today, we're</p> <p>13 going to be focused on the welfare economics of such</p> <p>14 markets.</p> <p>15 So what I mean by price as an investment is</p> <p>16 that there are a lot of interesting settings where it</p> <p>17 makes sense for companies to sacrifice current profit</p> <p>18 by setting a low price in order to generate volume</p> <p>19 that allows it to build some sort of dynamic resource.</p> <p>20 It's an investment in a dynamic resource that's at the</p> <p>21 heart of some type of competitive advantage. So an</p> <p>22 example might be accumulated know-how when there's a</p> <p>23 learning curve or an installed base of consumers when</p> <p>24 you have network externalities or switching costs.</p> <p>25 And I think these are interesting settings not</p>

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1 just from a competitive strategy perspective, but
 2 they're also interesting because they give rise to
 3 some policy questions. For example, in competition
 4 policy, you know, how should we be thinking about
 5 pricing below cost, when pricing below cost might
 6 really well be at the heart of a strategy to exploit
 7 the learning curve, for example? Or in industrial
 8 policy, how are we to think about subsidies, which are
 9 intended to help an industry take off in the face of
 10 these kinds of potential dynamic advantages?

11 And our view in this paper is that, you know,
 12 you really need a well formed understanding of the
 13 welfare economics of competition, of competition for
 14 the market in particular, in these settings in order
 15 to have a useful conversation about policy. So, for
 16 example, if unfettered dynamic competition for the
 17 market is fairly efficient, then perhaps there might
 18 be a relatively big downside to subsidies if you're
 19 trying to get the market to take off.

20 Now, you might say, well, hey, there's really
 21 nothing to see here; let's just move along. Maybe the
 22 welfare economics of price as an investment is
 23 actually fairly clear-cut. Yes, you have this jostle
 24 for advantage that results in low prices, at least in
 25 the short run. That's good, you might imagine, for

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1 consumers and society, and unlike a rent-seeking
 2 model, for example, the value here is not destroyed
 3 but presumably transferred to customers through low
 4 prices, and so it might be fairly clear-cut that
 5 competition for the market, when price serves as an
 6 investment, is likely to be pretty good for welfare.

7 But then when you think about it a little bit,
 8 you can see actually that there could be two sides to
 9 this. So on the one hand, competition for advantage
 10 through price could offset the market power that might
 11 typically arise in an oligopoly market. The
 12 competition for advantage might actually hasten the
 13 investment in these valuable resources, like
 14 cumulative know-how. And so you might imagine that
 15 the competition is likely to be at least if not
 16 inefficient, relatively inefficient.

17 On the other hand, we need to keep in mind that
 18 prices that are too low may actually cause deadweight
 19 losses, just as prices that are too high can cause
 20 deadweight losses, and in the dynamics of competition
 21 for the market, there might be an interplay -- perhaps
 22 a dysfunctional interplay -- with various problematic
 23 entry and exit dynamics. You might have coordination
 24 failures, for example, with respect to entry. You
 25 might have wars of attrition when it comes to exiting

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1 the market.

2 And then, finally, what we have found in other
 3 work that we've done is that when you have price as an
 4 investment, you can get pricing dynamics that look a
 5 lot like traditional notions of predatory pricing,
 6 where a firm prices low, a rival exits, and then the
 7 firm raises its price, and the long-run market
 8 structure turns out to be a monopoly. So it seemed to
 9 us at least to be an open question, how efficient is
 10 competition for the market when price serves as an
 11 investment, and that's really the focus of my talk
 12 today.

13 So the agenda here is to use what we call
 14 quantitative theory in the Ericson and Pakes 1995
 15 tradition to assess essentially how efficient
 16 competition for the market is when price serves as an
 17 investment. So we're going to analyze a discrete time
 18 stochastic gain. We are going to compute equilibria
 19 over a wide swath of parameter space to highlight the
 20 implications of the model for industry dynamics. We
 21 are then going to assess the deadweight losses that
 22 arise. We are going to assess them against what we
 23 hope are interesting benchmarks. And then we're going
 24 to anatomize the deadweight loss; that is to say, we
 25 are going to decompose it to try to figure out what's

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1 going on.

2 I actually have two objectives for this talk.
 3 The first is to say something, I hope, that's
 4 interesting about the welfare economics of competition
 5 when price serves as an investment. The second
 6 objective is to illustrate what I think is a research
 7 question for which quantitative theory is really well
 8 suited.

9 So, you know, we know in dynamic Markovian
 10 models, in the spirit of Maskin and Tirole, for
 11 example, that pretty much anything can happen. We
 12 want to push a little bit beyond that here because
 13 we're not just interested in what happens, but we're
 14 interested in magnitudes and the patterns that reside
 15 in what happens, and we think that this quantitative
 16 theory approach is a useful way to do that.

17 So we focus on one application in the paper,
 18 that is, learning-by-doing. This is both economically
 19 and empirically important. You can look at Levitt,
 20 List, and Syverson, for example, and the dozens and
 21 dozens of references in that paper to see the
 22 importance of learning-by-doing, and actually to see a
 23 very nice discussion of its role in endogenous
 24 productivity growth.

25 We know that learning-by-doing has given rise

85	<p>1 in the past to interesting pricing and market 2 structure dynamics. You can see this, for example, in 3 Benkard's 2004 paper on wide-body airframes. You can 4 see it more recently in a nice paper by Reichelstein 5 and Sahoo on solar panels.</p> <p>6 And learning-by-doing finally I think is 7 important and interesting to look at because the 8 policy implications, to quote Peter Thompson in his 9 recent handbook chapter in The Economics of 10 Innovation, is complicated. I am not going to read 11 the quote, but he talks about how there are 12 complicated issues around both competition policy and 13 industrial policy that arise when you have 14 learning-by-doing.</p> <p>15 So let me outline the model for you. I'll do 16 this fairly briefly. So we're going to look at, in 17 this paper, a discrete time/infinite 18 horizon/stochastic game. This is, by the way, the 19 framework that we have used in a variety of papers 20 that we've done over the last eight to ten years.</p> <p>21 So in the model we have the action, and the 22 time period is going to be broken down into two 23 phases. There's a price-setting phase and then an 24 entry/exit phase. A state for a firm in this model is 25 the firm's cumulative experience, except for when that</p>	87	<p>1 perspective, it's as if its rival is following a 2 randomized strategy, and so we describe exit and entry 3 behavior through an exit/no entry probability, denoted 4 by fee.</p> <p>5 In the pricing phase, here's the Bellman 6 equation for -- this is for firm one, if firm one is 7 in the industry. This gives me a chance to talk about 8 a couple of model primitives. There's a marginal cost 9 which determines -- which depends on the rate of 10 learning, which is captured by the progress ratio, R_0, 11 where higher values of R_0 correspond to faster 12 learning. There's a demand function, logit -- the 13 demand function is given by logit demand, the key 14 parameter in the demand function -- actually, the two 15 key parameters in the demand function.</p> <p>16 One is Σ, which is the degree of horizontal 17 differentiation, with zero being no horizontal 18 differentiation, perfect substitutes, and as Σ 19 gets bigger, these products become much more 20 differentiated and are close to being independent 21 demands. And then there's P_0, which is essentially 22 the marginal cost of the outside good. The price of 23 firm n is denoted by P_n as a function of the state, 24 and then U here is the continuation value after the 25 pricing phase.</p>
86	<p>1 state takes on -- that state variable takes on a value 2 of zero, which signifies that the firm is outside the 3 market. So basically the state space in this model is 4 a pair of states, because we have, at most, two firms.</p> <p>5 We're going to imagine here -- and this is 6 actually, I think, an important assumption in this 7 model -- that learning is proprietary. So the only 8 way that you gain cumulative know-how is by selling 9 stuff and producing it, and so there's no way that you 10 can catch up to a firm that has more cumulative 11 know-how than you do, other than to sell more stuff. 12 And if you're an entrant outside this market, we 13 assume that you have to start at the top of the 14 learning curve. We can talk more perhaps during Q&A 15 about what happens when that assumption gets relaxed.</p> <p>16 We have an entry/exit phase, as I said. If a 17 firm is outside the industry, it gets a draw of a 18 setup cost that's in a certain distribution with a 19 certain expectation. If the firm is an incumbent, it 20 gets a draw of a scrap value with a distribution as 21 well and an expectation. Both those expectations are 22 parameters in the model, as well as the support of the 23 distribution.</p> <p>24 And these setup costs and scrap values are 25 privately observed, and so from a rival firm's</p>	88	<p>1 So let me talk a little bit about the 2 equilibrium pricing condition that comes out of the 3 first-order condition. So there really are three 4 pieces to this condition. There's first a piece that 5 reflects static profit. That's sort of the usual 6 marginal cost plus markup. Then there's something 7 that we call the advantage building motive. The 8 advantage building motive is essentially the marginal 9 value -- the marginal future value of improving one's 10 own competitive position. This kind of term would 11 arise in a monopoly model, for example.</p> <p>12 And then there's a term that would not arise in 13 a monopoly model, and that's the advantage-denying 14 motive. This is the marginal future value of 15 preventing your rival from improving its competitive 16 position, and this is a term that not only doesn't 17 arise in a monopoly model, it does not arise in the 18 social planner's model that I'll talk about in a 19 moment.</p> <p>20 This advantage-denying motive is interesting. 21 Similar terms, analogous terms arise in other papers 22 on learning-by-doing, other papers on network 23 externalities, switching costs, and habit formation. 24 So this is a term that kind of goes beyond this 25 particular application. In this application, you can</p>

89	<p>1 see that the advantage-denying motive is actually</p> <p>2 weighted by the diversion ratio, so in an environment</p> <p>3 with a low diversion ratio, the advantage-denying</p> <p>4 motive will be less important.</p> <p>5 The advantage-denying motive in our 2014 paper,</p> <p>6 we talked about how the advantage-denying motive is a</p> <p>7 really important reason why you get what in a moment</p> <p>8 I'm going to call aggressive equilibria, equilibria</p> <p>9 that look like predatory pricing.</p> <p>10 Let me talk a bit about our computational</p> <p>11 approach. So we're going to focus on symmetric Markov</p> <p>12 perfect equilibria, and we're going to compute them.</p> <p>13 We're also going to compute the first-best planner's</p> <p>14 problem as well. The planner's problem is to maximize</p> <p>15 total surplus, taking into account entry costs and</p> <p>16 scrap values for exit, and we're going to do these</p> <p>17 computations by -- when we -- as we vary four key</p> <p>18 parameters: the learning rate R_0, the product</p> <p>19 differentiation parameter Σ, the expected scrap</p> <p>20 value, x-bar, and the marginal cost of the outside</p> <p>21 good, P_0. We are going to use the homotopy method</p> <p>22 that we talk about in our 2010 paper to do this.</p> <p>23 What we essentially do is we look at six</p> <p>24 two-dimensional slices of parameter space, and I want</p> <p>25 to say just a little bit about the ranges that we</p>	91	<p>1 model.</p> <p>2 So what we tried to do in choosing those upper</p> <p>3 limits is to avoid representing essentially identical</p> <p>4 economic environments. So the acid test that we used</p> <p>5 was, well, if we increase Σ a little more, does it</p> <p>6 change things very much? And if it doesn't, then that</p> <p>7 would be outside that upper bound.</p> <p>8 So we ended up doing computations for a little</p> <p>9 over 2000 distinct parameterizations. That resulted</p> <p>10 in about 68,000 different symmetric Markov perfect</p> <p>11 equilibria. Some parameterizations had hundreds of</p> <p>12 MPE, what my colleague Mark Satterthwaite refers to as</p> <p>13 the rat's nest of equilibria, and so I'm going to give</p> <p>14 you -- show you results over the space that we</p> <p>15 examined.</p> <p>16 So the first thing I want to talk about is a</p> <p>17 typology of equilibria. So the equilibria tended to</p> <p>18 be one of two types, what we call an accommodative</p> <p>19 equilibrium and an aggressive equilibrium. These</p> <p>20 equilibria, for the same parameterization, involved</p> <p>21 quite different MPE policy functions and implied</p> <p>22 oftentimes quite different market dynamics and</p> <p>23 performance.</p> <p>24 Let me give you an example for one particular</p> <p>25 parameterization. So this is a parameterization that</p>
90	<p>1 choose in our computations, because in the paper, we</p> <p>2 report a lot of frequencies. You know, this</p> <p>3 percentage of time of all parameterizations, this is</p> <p>4 what happens. So we had to really be mindful of how</p> <p>5 we thought about the parameter choices, because we're</p> <p>6 doing, like, lots and lots of computations here.</p> <p>7 So we tried to make the ranges of these</p> <p>8 parameters, when possible, to reflect their natural</p> <p>9 economic values. That would be clearest in the case</p> <p>10 of R_0, which ranges from zero to one. We want to</p> <p>11 essentially ensure that we have some interesting</p> <p>12 economic environments, so we chose the range of X-bar</p> <p>13 to ensure that whatever its value is, that there was</p> <p>14 always some degree of sunkness with respect to entry,</p> <p>15 that entry costs were always to some extent sunk.</p> <p>16 We tried to span interesting economic</p> <p>17 environments, so the range for Σ is going to</p> <p>18 essentially map us from perfect substitutes to</p> <p>19 essentially independent demands. And then, finally,</p> <p>20 what was perhaps most difficult was figuring out what</p> <p>21 the upper bound should be for those parameters, in</p> <p>22 particular P_0 and Σ, that had no natural upper</p> <p>23 bound. We had to put some limits, after all, on the</p> <p>24 number of computations that we can do, because it's</p> <p>25 computation -- this is a computationally expensive</p>	92	<p>1 actually gave rise to three symmetric MPE. By the</p> <p>2 way, we don't know for sure whether we can compute all</p> <p>3 the MPE. I mean, we do our best to find as many as we</p> <p>4 can, but we -- I can't assure you, and we don't have a</p> <p>5 theorem that tells you, that we have found all of</p> <p>6 them.</p> <p>7 This particular parameterization involved three</p> <p>8 MPE. In the aggressive equilibrium, let me tell you</p> <p>9 what the modal dynamics in that equilibrium look like.</p> <p>10 Both firms essentially entered an empty industry</p> <p>11 almost right away. Then they battled furiously on</p> <p>12 price, and at some point, one firm gains a cost</p> <p>13 advantage, and at that point, there's a positive</p> <p>14 probability that the rival in equilibria will exit.</p> <p>15 That exit ends up taking about four or five periods.</p> <p>16 When exit occurs, the remaining firm will raise its</p> <p>17 price up to a level that equals approximately the</p> <p>18 monopoly price corresponding to the marginal cost at</p> <p>19 the bottom of the learning curve. If you were to look</p> <p>20 at that kind of, well, what would that look like in</p> <p>21 the real world, it would resemble -- it would sort of</p> <p>22 resemble kind of traditional notions of predatory</p> <p>23 pricing.</p> <p>24 The other MPE, actually the second of the three</p> <p>25 MPE, is an accommodative equilibrium -- I should</p>

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1 mention that the third MPE, which I'm not going to
 2 talk about, is sort of in between these two. The
 3 third equilibrium -- the accommodative equilibrium
 4 involves, again, both firms entering right away,
 5 virtually. One firm temporarily gains an advantage,
 6 moves down its learning curve a little. The rival,
 7 though, stays in the market. It tries to make sales.
 8 Eventually it begins to make sales, and eventually it
 9 catches up with what had been a temporary leader of
 10 the market.

11 And then beyond that point, the two firms march
 12 their way in tandem down the learning curve, and they
 13 do so charging the duopoly price that -- the Nash
 14 equilibrium price that roughly corresponds to the
 15 marginal cost at the bottom of the learning curve.
 16 And you can see that the performance of these
 17 equilibria are quite different. In the long run, in
 18 the aggressive equilibrium, we virtually have one
 19 firm, an expectation. In the accommodative
 20 equilibrium, we're almost certain to have two firms,
 21 very different expected long-run prices.

22 By "long-run" here, I mean imagine how the
 23 transient distribution implied by the dynamics implied
 24 by the equilibrium policies, imagine how that goes in
 25 the limit, and then take expectations over that

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1 distribution, and you can see the expected time to
 2 maturity; that is to say, to get to the bottom of the
 3 learning curve is very different in those two
 4 equilibria.

5 So this distinction between aggressive and
 6 accommodative coincides closely, although not
 7 perfectly, in those situations where we have multiple
 8 equilibria, the equilibria that have the lowest
 9 deadweight loss and those that have the highest
 10 deadweight loss. So I am going to use the terms "best
 11 equilibrium" and "worst equilibrium" to correspond to
 12 a case where we have multiple equilibria, and there is
 13 a difference in the deadweight losses, which there
 14 always is.

15 So here's what we get. Now, the deadweight
 16 loss numbers themselves actually don't mean anything
 17 as absolute magnitude, so it's useful to compare them
 18 to some benchmark. The benchmark that we use is what
 19 we call industry value added. Industry value added is
 20 essentially the total surplus that arises in this
 21 market from the planner's problem, from first-best
 22 surplus maximization, minus the surplus that would
 23 arise in an empty industry when the only thing that
 24 you have available to consumers is the outside good.
 25 So the accommodative equilibrium's relative deadweight

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1 loss is about 4 1/2 percent. The aggressive
 2 equilibrium deadweight loss is about 13 percent.

3 And then here are some benchmarks. For
 4 example, in a dynamic model, if we essentially force
 5 firms to be myopic, that is to say, we turn off the
 6 investment rule of pricing, the deadweight loss
 7 becomes about 16.7 percent. If we have a dynamic
 8 model where we, in effect, turn off noncooperative
 9 behavior -- that is to say, we allow firms to collude
 10 on price but still act noncooperatively in terms of
 11 entry/exit behavior -- the deadweight loss is about
 12 16.4 percent.

13 If you turn off both of these, turn off the
 14 investment rule of pricing and noncooperative pricing,
 15 the deadweight loss is 28 percent. And then with full
 16 collusion, collusion on both price and on entry/exit
 17 behavior, the deadweight loss is about 14 percent.

18 So a couple of observations. One is that
 19 there's nothing in the primitives here that suggest to
 20 us that the deadweight loss should be in any sense
 21 low, and the other thing that's noteworthy is that
 22 turning off the investment rule of pricing is actually
 23 slightly more damaging than turning off noncooperative
 24 behavior, which suggests that the investment rule of
 25 pricing might be a strong force in this model for

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1 efficiency.

2 So here's some data on the -- summaries of data
 3 on the deadweight loss for all parameterizations.
 4 This is -- the first table is relative deadweight loss
 5 for all MPE. The median relative deadweight loss is
 6 about 7.7 percent. For the best MPE, 5.7 percent.
 7 For the worst, 9.2 percent. And in the majority of
 8 parameterizations -- and in some cases a long majority
 9 of parameterizations -- these deadweight losses are
 10 less than 10 percent.

11 Here's another benchmark we can compare the
 12 deadweight loss to some what we think are interesting
 13 counterfactuals. So, for example, if we turn off the
 14 investment rule of pricing and we force firms to
 15 essentially be myopic and we look at the ratio of the
 16 deadweight loss in that model to the deadweight loss
 17 in an equilibrium, the median of that ratio is 1.78,
 18 and the percent of parameterizations where that is
 19 bigger than 2 is about 44 percent. The deadweight
 20 loss relative to collusion looks a little bit lower,
 21 but still the ratio there is well over 1, 1.44.

22 Here's another view. This is showing you
 23 pictures of each of the six slices that we take where
 24 we've shaded in higher relative deadweight loss in
 25 darker and darker colors, and if you glimpse hard

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1 enough and stare at this a while -- well, actually,
2 you don't have to stare at this for very long to see
3 that anything can happen. There are no unambiguous
4 comparative static results in this model with respect
5 to these parameters, at least.

6 If you stare at this a little bit, you can
7 begin to see that there is a tendency, although it
8 doesn't happen always, for the deadweight loss to be
9 lower as the learning rate gets closer to zero, as
10 learning gets faster. And by the way, these are
11 relative deadweight losses averaged over all types of
12 equilibria.

13 So some tentative observations. The best
14 equilibria, which are usually accommodative, seem
15 reasonably efficient. The worst equilibria, which are
16 usually aggressive, are not great, but they're still
17 more efficient than if firms ignore the investment
18 rule of pricing and somewhat more efficient than if
19 the firms colluded. And finally, as I mentioned,
20 faster learning, lower progress ratio, does seem to
21 tend toward a lower relative deadweight loss.

22 So dynamic price competition seems reasonably
23 efficient or at least not too inefficient, even though
24 there are nontrivial distortions that arise in
25 equilibrium. There are too low prices in some states.

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1 There are almost always too many firms in the short
2 run, whatever the type of equilibrium is. There's
3 overentry. There are sometimes, especially in
4 accommodative equilibria, too many firms in the long
5 run, so there's underexit. And the learning is too
6 slow relative to what a social planner would like to
7 achieve.

8 So why is this going on? What is at the heart
9 of what seems to be a relatively efficient market
10 outcome, or at least reasonably inefficient or not too
11 inefficient market outcome, but yet with these sorts
12 of distortions?

13 So what we do is we try to anatomize the
14 deadweight loss. So just to remind you here, the
15 deadweight loss is going to be the difference between
16 the expected NPV of total surplus that arises in the
17 planner's problem, which is the maximum level of total
18 surplus, and the level of total surplus that arises in
19 equilibrium.

20 The deadweight loss, if you think about it in
21 this model, is really shaped by three things. One is
22 that the equilibrium policy function can differ from
23 the first-best policy function with respect to price.

24 The equilibrium policy function with respect to
25 entry/exit can differ from the first-best policy

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1 function with respect to entry/exit. And finally,
2 those two behaviors can imply different market
3 dynamics.

4 So, in other words, statewide, the deadweight
5 loss is going to be shaped by differences in static
6 surplus. It's going to be shaped by differences in
7 receipts minus outlays from entry/exit behavior. And
8 it's going to be shaped by differences in the
9 likelihood that the industry tends to evolve toward
10 inherently high total surplus states. So we basically
11 take that intuition and we decompose the deadweight
12 loss into three pieces.

13 There's what we call the pricing distortion,
14 which captures the expected value, in effect,
15 discounted over time, in statewide differences in
16 static surplus. There's the entry/exit distortion,
17 which captures differences over time and expectation
18 between differences in receipts and outlays from entry
19 and exit -- exit and entry. And then, finally,
20 there's the market structure distortion, which
21 captures differences in the way in which the industry
22 evolves over time.

23 So real quick statistics on the regularities.
24 There's a positive -- typically positive pricing
25 distortion which says -- which is a sign of two

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1 things, actually, that are intertwined to some degree.
2 It tells us that there's a lot of market power going
3 on or there's some market power going on and there's
4 also an inefficiency in which these firms are using
5 price as an investment. There's a positive entry/exit
6 deadweight loss, which tells us that firms in
7 equilibrium tend to have higher outlays for setup
8 costs and lower receipts for scrap values.

9 And there's, interestingly, a negative
10 deadweight loss component for market structure, which
11 tells us that the equilibrium tends to place more mass
12 on high-surplus states than the planner's solution
13 does, which is telling us, we think, that the gains in
14 this model typically from product variety are
15 outweighing the losses from too slow learning.

16 So why is the best equilibrium reasonably
17 efficient? There actually are two reasons for this,
18 which we capture in -- the first of which we capture
19 in a proposition, which basically places a bound on
20 the static distortion on a state-by-state basis, and
21 we argue that this bound actually has bite. As
22 incumbent firms move down the learning curve, the part
23 of this bound that involves D_0 is going to go down
24 faster than the square of the margin, because
25 essentially what's happening, as the firms move down

101	<p>1 the learning curve, is they're really marginalizing</p> <p>2 the viability of the outside good.</p> <p>3 As they become more cost-efficient, they're</p> <p>4 facing less competitive pressure from substitutes, and</p> <p>5 the industry demand in this case is becoming less</p> <p>6 price-elastic. In effect, what's happening is that</p> <p>7 the Harberger triangle is being squeezed. That's the</p> <p>8 first reason.</p> <p>9 The second reason is that for intermediate</p> <p>10 levels of product differentiation, the accommodative</p> <p>11 equilibria tend to have more firms -- two firms, in</p> <p>12 particular -- in a market, whereas the first-best</p> <p>13 solution tends to have one firm in the market, and</p> <p>14 that tends, on the downside, to make the deadweight</p> <p>15 loss component from entry/exit to be positive, but it</p> <p>16 also serves to reduce the market structure component,</p> <p>17 and in some cases that reduction can be large enough</p> <p>18 that, in fact, that market structure component becomes</p> <p>19 negative and offsets the entry/exit distortion.</p> <p>20 And we actually show in the paper that the</p> <p>21 gross benefit from product variety is going to be</p> <p>22 enhanced as learning economies strengthen, and that</p> <p>23 works to limit what we call the nonpricing distortion,</p> <p>24 which is the sum of the entry/exit distortion and the</p> <p>25 market structure distortion.</p>	103	<p>1 economies essentially enhance the value of having too</p> <p>2 many firms in the market. And in the worst</p> <p>3 equilibria, the learning economies help the bound on</p> <p>4 the monopoly pricing distortion have some degree of</p> <p>5 bite.</p> <p>6 What are the implications for policy? Well, in</p> <p>7 34 seconds, it's difficult to talk about all of them.</p> <p>8 We hope that there are some interesting ones. I'll</p> <p>9 mention my own view about this, though. I don't see</p> <p>10 this as a paper that would justify laissez-faire. You</p> <p>11 certainly would want to have -- this is obvious, I</p> <p>12 think -- but you certainly would want to prevent</p> <p>13 collusion in this kind of market. You probably would</p> <p>14 want to prevent markets -- we want to prevent firms</p> <p>15 from engaging in exclusionary behavior that would</p> <p>16 prevent this kind of competition from occurring in the</p> <p>17 first place.</p> <p>18 You may want to think about in this kind of</p> <p>19 market things that you could do to make learning less</p> <p>20 proprietary. So, for example, limitations on</p> <p>21 noncompete clauses that might make it difficult for</p> <p>22 workers that have knowledge embedded in them from</p> <p>23 moving firm to firm. I think an interesting direction</p> <p>24 going forward with this research agenda is to explore</p> <p>25 in more detail some of these policy implications.</p>
102	<p>1 Why are the worst equilibria not too</p> <p>2 inefficient? Well, one reason is that these</p> <p>3 equilibria tend to evolve very quickly toward</p> <p>4 monopoly, and when these aggressive equilibria arise,</p> <p>5 they tend to be in circumstances where the first-best</p> <p>6 solution is actually to have one firm in the market.</p> <p>7 In addition, we also show in the paper that the</p> <p>8 monopoly pricing distortion is bounded, and we argue</p> <p>9 that this bound actually has bite, first of all as</p> <p>10 firms move down the learning curve, and secondly, it</p> <p>11 has bite in those circumstances that actually give</p> <p>12 rise to aggressive -- or an important set of</p> <p>13 circumstances that give rise to aggressive equilibria;</p> <p>14 namely, when there is not very much product</p> <p>15 differentiation in the market.</p> <p>16 So, wrapping up, dynamic price competition, we</p> <p>17 conclude in the paper, is for sure not fully</p> <p>18 efficient, but it's reasonably so. There's reasonable</p> <p>19 efficiency despite equilibrium policy functions that</p> <p>20 differ very much from the first-best policy functions.</p> <p>21 We conclude that learning-by-doing plays an important</p> <p>22 indirect role in containing these inefficiencies. In</p> <p>23 the best equilibrium, it contains the pricing</p> <p>24 distortion by working to marginalize the outside good.</p> <p>25 Despite overentry in the best equilibria, the learning</p>	104	<p>1 Maybe the one that I'm especially interested in is</p> <p>2 doing something around industrial policy.</p> <p>3 Thank you.</p> <p>4 (Applause.)</p> <p>5 MS. CARLSON: So we have time for maybe one or</p> <p>6 two questions, if there are any questions for</p> <p>7 Dr. Besanko.</p> <p>8 MR. BESANKO: Yes, Eric.</p> <p>9 MR. RASMUSEN: (Off mic.)</p> <p>10 MR. BESANKO: Identical cost functions -- the</p> <p>11 question was, in the model, are there identical cost</p> <p>12 functions except for the setup costs. They are --</p> <p>13 they are identical de novo, but once firms start to</p> <p>14 move down the learning curve at different rates, then</p> <p>15 those marginal costs become different.</p> <p>16 MR. RASMUSEN: Oh, okay. You have got a lot</p> <p>17 going on already.</p> <p>18 MR. BESANKO: So, yeah, there's an endogenous</p> <p>19 degree of asymmetry between these firms.</p> <p>20 MR. RASMUSEN: Yeah. But for policy purposes,</p> <p>21 it would be important to think about where you don't</p> <p>22 know your marginal cost in advance, because that's a</p> <p>23 usefulness of the war of attrition afterwards --</p> <p>24 MR. BESANKO: Absolutely. So I think -- I</p> <p>25 don't have time to talk about sort of quantitative</p>

105	<p>1 theory writ large, that I think would be an 2 interesting discussion, but I do think one interesting 3 question for quantitative theory -- whether our 4 computing abilities are up to the task is less 5 clear -- would be to have models where you have 6 asymmetric information, where other states would 7 include, you know, beliefs about information that the 8 other parties in the game have. I think that's a 9 problem. Asymmetric information in these models, 10 besides kind of the simple asymmetric information that 11 we have around entry costs and scrap values, I think 12 would be a good direction to go. 13 MR. RASMUSEN: That's too hard for you, but 14 what you can do is symmetric unknown marginal costs, 15 where everybody finds out once you get in. 16 MR. BESANKO: Yes, absolutely. 17 MR. BRUESTLE: Steven Bruestle, Federal 18 Maritime Commission. 19 I'm particularly interested in your policy 20 implementations as to whether or not we should 21 increase or try to increase or decrease 22 learning-by-doing. So it seems like there's forces 23 that could go either way. Do you think, in general, 24 we want to increase or decrease learning-by-doing in 25 firms?</p>	107	<p>1 which uses this kind of technology, if you will, for 2 merger analysis. They don't look at 3 learning-by-doing, but they actually look at capital 4 accumulation, and in their model, the antitrust 5 enforcer is an active player, and so I think that's a 6 useful direction. 7 We thought a little bit about that with respect 8 to an enforcer who was going to be policing things 9 that could be considered exclusionary, but I think 10 that's a useful direction, maybe especially for, you 11 know, effecting learning-by-doing. 12 MR. BRUESTLE: Thank you. 13 MS. CARLSON: Thank you. 14 (Applause.) 15 MR. WILSON: Thanks very much, everyone. If 16 you are interested in lunch, there should be things 17 set out to my left, along the back wall. Thank you 18 very much. We will reconvene in about 30 minutes for 19 the afternoon sessions. 20 (Whereupon, at 11:59 a.m., a lunch recess was 21 taken.) 22 23 24 25</p>
106	<p>1 MR. BESANKO: That's -- so I don't want to 2 speculate too much about that. We do find this 3 general tendency that faster learning makes the market 4 more efficient, lower deadweight losses. 5 MR. BRUESTLE: Okay. 6 MR. BESANKO: There's something to be said for 7 things that you could do outside the model here that 8 would lower progress ratios generically. 9 MR. BRUESTLE: Hmm. 10 MR. BESANKO: You know, so how do workers 11 learn? How do they learn -- how do they learn more 12 quickly? How do firms learn? So I think there's a -- 13 that's all a black box in our model that I think would 14 be interesting to kind of try to break open a little 15 bit. 16 MR. BRUESTLE: So have you thought of maybe 17 looking at maybe a government endogenously setting 18 learning-by-doing and seeing what level they would 19 want to set? 20 MR. BESANKO: I would love to have, in a model 21 like this, the Government as an actor. Actually, 22 there is a very -- we have not done that. I would 23 love to go in that direction. There is a very 24 interesting paper that's going to be coming out in the 25 JPE by Mermelstein, Nova, Satterthwaite, and Winston,</p>	108	<p>1 AFTERNOON SESSION 2 (12:31 p.m.) 3 PAPER SESSION: 4 THE EFFECT OF PRODUCT MISPERCEPTION ON ECONOMIC 5 OUTCOMES: EVIDENCE FROM THE EXTENDED WARRANTY MARKET 6 - - - - - 7 MR. ROSENBAUM: All right, everyone. I hope 8 everyone's enjoyed their lunch. We're now going to 9 get started with the afternoon sessions. So the first 10 thing we have up is a paper session chaired by myself 11 and my colleague Ted Rosenbaum of the FTC. 12 Our first paper will be by Jose Miguel Abito. 13 He will be discussing the effect of product 14 misperception on economic outcomes. 15 Jose? Well, maybe we will be taking a slightly 16 longer lunch break for just a minute or so. I hope 17 everyone's having a good day. I appreciate you 18 hanging out inside. 19 (Pause in the proceedings.) 20 MR. ABITO: Sorry about that. We were 21 finishing lunch. 22 So this paper is -- first of all, thanks for 23 accepting the paper, and this work is joint with Yuval 24 Salant from Northwestern and Kellogg, so everybody is 25 kind of -- I graduated from Northwestern, so there is</p>

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1 a lot of, like, Northwestern connections here.
 2 Okay, so this paper is about extended
 3 warranties. Probably most of you are familiar with
 4 extended warranties, but just in case you haven't
 5 heard someone selling extended or you haven't
 6 encountered anybody trying to sell the extended
 7 warranty, so the way we would think about extended
 8 warranties is that it's an insurance product that
 9 protects you against failure of a durable good. So
 10 popular examples of extended warranties are you have
 11 extended warranties on vehicles, you have extended
 12 warranties on electronic goods. So we are going to
 13 specifically focus on TVs in this project, okay?
 14 So what's interesting about extended warranties
 15 is actually -- and one that raises concern -- is that
 16 typically when you're buying, let's say, a TV, you do
 17 a lot of research about a TV with different kinds of
 18 brands and, you know, what features they have, but
 19 you -- at least, you know, it's rare that you actually
 20 think about these extended warranties or even have
 21 that as part of your decision-making.
 22 And usually for these products you actually --
 23 even though you're aware of extended warranty, you
 24 actually don't know, you know, the terms of extended
 25 warranties and specifically the price. So typically a

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1 salesperson, after convincing you that this product is
 2 so great and, you know, you should buy it, actually
 3 right before you are going to pay for the product,
 4 they would say, oh, you know what, it might actually
 5 break down and, you know, here's an extended warranty
 6 for X dollars, and it's going to cover you for two
 7 more -- well, they don't say it's two more years than
 8 the manufacturer's warranty. They always say, like,
 9 it's three years, okay? So it's usually offered at
 10 the point -- all the information that you may have as
 11 a consumer actually happens at the point of sale.
 12 So extended warranties are pretty popular. One
 13 is that they're very expensive, and if you ask --
 14 like, when I was starting this project, like, whenever
 15 I asked my colleagues or talked to them that I work on
 16 extended warranties, they would say, well, who the
 17 hell is going to buy those extended warranties, okay?
 18 So, in fact, the conventional wisdom is that, you
 19 know, these are very expensive and mostly useless
 20 products, okay? So you even have, like, the Samsungs
 21 and -- you know, talking about extended warranties,
 22 and kind of like that's the general idea about, you
 23 know, the value of these extended warranties.
 24 But despite that, okay, it's very profitable.
 25 We weren't actually aware of it. Thanks to Yuval's

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1 student who worked for a consulting company and wanted
 2 to get some brownie points from Yuval, we actually
 3 found out that it's very, very profitable. And, of
 4 course, the companies -- you know, the retailer -- the
 5 big box stores didn't want that to be advertised,
 6 okay?
 7 So, for example, in the U.S., okay, almost half
 8 of Best Buy -- in fact, I think I have seen a number
 9 that's more than half of Best Buy's operating income
 10 actually comes from extended warranties, and, in fact,
 11 the way this -- you know, the way this -- the way
 12 these are sold actually may be the reason why these
 13 big box stores, if they still exist, are still
 14 existing, okay? And the profit margins on extended
 15 warranties can range from 50 to 60 percent, okay?
 16 So in the UK, which was relatively more active
 17 in terms of investigating the market, okay, they
 18 estimated -- when they looked at this market, they
 19 estimated that for the top five electronic retailers,
 20 they earn roughly, like, 100 million pounds annually,
 21 okay? So we wanted to understand this market more,
 22 so, you know, we have a lot of preconceived notions of
 23 what this market is, but we wanted to go to the data,
 24 and, in fact, we were pretty surprised that, in fact,
 25 the significant fraction of people actually buy these

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1 products.
 2 For example, one of -- one out of four, like 25
 3 percent of TV buyers actually do purchase extended
 4 warranties on TVs. So that's what we saw in the data,
 5 and, of course, confirming what we already know, the
 6 margins are pretty big, okay? So, for example, on
 7 average -- also, so this one out of 24 is for TV, but
 8 then you -- it actually -- it's actually the same, so
 9 roughly 30 to 40 percent across different product
 10 categories, okay? So some products you would think,
 11 oh, it might be worth buying extended warranties, but
 12 other products, you pretty much think it's of no
 13 value.
 14 The margins are big, especially if you compare
 15 that to the actual failure rates, okay? So the
 16 failure rates was about 7 percent, but then the way --
 17 the price of the extended warranty is roughly, like,
 18 20, 25 percent of the -- the price of the extended
 19 warranty is about 20 to 25 percent of the price of the
 20 good itself, okay? So that's one question.
 21 Another thing is that -- why we're interested
 22 in it is that, you know, it has caught -- because it
 23 is very profitable, but at the same time, you know, a
 24 little bit dubious in value, competition authorities,
 25 okay, or agencies have started or at least caught

113	<p>1 their attention and actually tried to do something in</p> <p>2 terms of, like, understanding this market.</p> <p>3 So, for example, the FTC, one thing that they</p> <p>4 have a page talking about, okay, what you should do</p> <p>5 when you -- you know, when you're faced with a</p> <p>6 salesperson who's trying to sell you extended</p> <p>7 warranty, and basically the main message here is try</p> <p>8 to think first before you actually buy. So they</p> <p>9 really, like, okay, they -- in the website, they would</p> <p>10 say, okay, you might actually not benefit from it,</p> <p>11 okay? Stop, think about that, okay? Maybe it doesn't</p> <p>12 really need returns or repairs, or, in fact, the</p> <p>13 potential costs, expected costs are actually pretty</p> <p>14 low. So, you know, stop first before you think, but</p> <p>15 that's it.</p> <p>16 In the UK, they're more active. They actually</p> <p>17 did a thorough investigation in the early -- in 2003.</p> <p>18 What they concluded is that there's insufficient</p> <p>19 competition, mainly because how these extended</p> <p>20 warranties were being sold, and there's also -- they</p> <p>21 did mention there's a lack of information, but mostly</p> <p>22 they focus on the Competition Act.</p> <p>23 And, in fact, around I think 2011, what they</p> <p>24 did to address that or what they think that could help</p> <p>25 address that problem is that they forced or they</p>	115	<p>1 is it something about the buyer himself? Is it that</p> <p>2 they're very risk-averse and, therefore, they're</p> <p>3 willing to buy these contracts, okay? Or is it</p> <p>4 something -- what we are going to explore as what you</p> <p>5 call probability distortions or, simply said, there's</p> <p>6 something about how they misperceive or how they kind</p> <p>7 of distort the decision-making process that they have</p> <p>8 when they're evaluating the value of these warranties.</p> <p>9 So we're going to look at these different</p> <p>10 explanations and see, you know, which one is more</p> <p>11 likely explaining it. Then once we have -- and what</p> <p>12 we are going to see is that these probability</p> <p>13 distortions is actually driving this business, okay,</p> <p>14 this market, and -- but it's actually going to be</p> <p>15 important to understand what actually is probability</p> <p>16 distortion, what's driving probability distortion in</p> <p>17 the first place. So we're going to -- we have these</p> <p>18 two explanations, which is overestimation and</p> <p>19 overweighing, okay? And we're going to talk about it</p> <p>20 a little bit more once we reach that question.</p> <p>21 And then why do we care about the mechanism,</p> <p>22 okay? Well, again, it's to actually put scope and the</p> <p>23 rationale for intervention in the first place, okay?</p> <p>24 And once we establish that there is some scope and</p> <p>25 rationale for intervening in this market, then we have</p>
114	<p>1 required all the big retailers in the UK to actually</p> <p>2 post their extended warranty price on the website. So</p> <p>3 there is this price comparison website. When you buy</p> <p>4 a TV, you will go there, type your TV, and then you</p> <p>5 see all the extended warranty prices and terms of all</p> <p>6 the big retailers in the UK. So that's kind of like</p> <p>7 their way of remedying this apparent problem, okay?</p> <p>8 So our paper answers -- tries to answer these</p> <p>9 three research questions. One is, why is it very --</p> <p>10 why is the extended warranty business very profitable?</p> <p>11 The second is that what drives -- you know, what's the</p> <p>12 underlying mechanism? Once we kind of understand</p> <p>13 what's going on, what's the underlying mechanism? And</p> <p>14 tied to that is that, okay, once we understand the</p> <p>15 mechanism, can we actually do something about it,</p> <p>16 okay?</p> <p>17 So there's these three questions, first about</p> <p>18 profitability, and the way we're trying to think about</p> <p>19 or trying to answer this question is that we're going</p> <p>20 to explore factors at the buyer and the seller sides</p> <p>21 in particular. And is it about market power? Is it</p> <p>22 because of the fact that they essentially have a</p> <p>23 monopoly on these consumers who are presented with</p> <p>24 this product at the point of sale?</p> <p>25 Is that the reason why it's so profitable, or</p>	116	<p>1 to think about what tools should we use, okay? We are</p> <p>2 going to focus on two tools reflecting the fact that</p> <p>3 we're at the FTC, so we are going to think about</p> <p>4 competition policies, okay, and also what we call</p> <p>5 consumer policies, okay, something that addresses more</p> <p>6 about the decision-making process of buyers, okay?</p> <p>7 So let's go to the first question. Why is it</p> <p>8 profitable? To answer this question, we go to the</p> <p>9 data, okay? So this is pretty well known data set, at</p> <p>10 least in the operations/marketing crowd as well, and</p> <p>11 so it's data coming from a big U.S. electronics</p> <p>12 retailer. We don't know what it is, okay, but you</p> <p>13 know how many stores they have, and you can kind of,</p> <p>14 like, figure out which one it was, okay? So we think</p> <p>15 it's Best Buy, but, you know, what do we know? So</p> <p>16 it's a U.S. -- a major U.S. electronics chain, okay?</p> <p>17 So we see data from -- oh, so we have data on</p> <p>18 about 45,000 transactions, okay, and these</p> <p>19 transactions involve potential purchase of extended</p> <p>20 warranties. So the data contains everything that's</p> <p>21 being sold by these retailers, so it's across</p> <p>22 different product categories, okay? And then we have</p> <p>23 about 20,000 households, it's a panel, and so the data</p> <p>24 follows these 20,000 households from 1998 to 2004.</p> <p>25 What's interesting about this data is that --</p>

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1 so this extended warranty attachment rate is basically
 2 how many of those who bought a TV actually bought an
 3 extended warranty as well. So across product
 4 categories, that's about 29 percent, okay? And, of
 5 course, there's variation within categories or across
 6 categories. And the ratio between the extended
 7 warranty price and the product price is about 24
 8 percent, so they are being priced as 24 percent of the
 9 price of the product, okay?
 10 So we are going to focus on TVs because we know
 11 a little bit about the failure rates of these TVs,
 12 okay? For the statistics of TVs, okay, it's about 27
 13 percent attachment rate, price ratio is 22 percent,
 14 and average failure rate is around 7 percent. So the
 15 whole paper is going to be focusing on TV purchases,
 16 okay?
 17 All right. So although this data is from '98
 18 to 2004, okay, if you actually -- we went back to,
 19 like, Best Buy and the other stores, and we looked at
 20 their prices. Practically, you know, they're still
 21 charging the same high amount, 20 to 24 percent, and
 22 actually failure rates have decreased, okay? So it's
 23 not that, you know, that a lot has changed, at least
 24 in how they're pricing these goods, okay?
 25 So given the data and given our intention in

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1 terms of -- or our approach in terms of answering this
 2 question, so remember, we want to see whether it's
 3 about market power, is it about -- something about
 4 consumer decision-making, okay? In particular, for
 5 consumer decision-making, we need a model where you
 6 have risk -- standard risk aversion, so something
 7 that's related to the curvature of your utility, okay,
 8 and this notion of distorted probabilities, okay? So
 9 we're basically following what's in the literature.
 10 So there's this nice AER paper by Barseghyan,
 11 Molinari, O'Donohue, and Teitelbaum. So they look at
 12 home and auto loans, and they have this model. So
 13 this model tries to explain, oh, is purchases of these
 14 insurance contracts driven by standard risk aversion
 15 or is it something about the way they're thinking
 16 about the probability that you would need or you would
 17 use these contracts?
 18 So here let's focus on the utility of not
 19 buying extended warranties, so this is where the
 20 nonstandardness actually arises. So Φ is the
 21 probability of failure, the actual probability of
 22 failure. So you're -- the -- typically, okay, so when
 23 we're computing the utility of when you don't buy
 24 extended warranty or insurance contract, okay, with
 25 some probability, Φ , you are going to lose the value

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1 of the good or you have to replace it or you have to
 2 have it for repair, so you're going to have a -- incur
 3 some repair cost, let's say P over there, but with the
 4 other -- with the other probability, nothing is going
 5 to happen, so you go back and, you know, you have to
 6 incur your -- you know, your repair cost.
 7 But if you do buy an extended warranty, so
 8 regardless of what happens to the good, you are always
 9 covered, but in exchange, you have to pay a price, t ,
 10 okay? So here we are going to use this model. We are
 11 going to estimate this model and basically estimate
 12 risk aversion and this function, Ω . So this
 13 function, Ω , is what really -- is what the
 14 consumer is using when they're evaluating the value of
 15 not buying the extended warranties, and so instead of
 16 taking the actual probabilities as weight -- as the
 17 weight in thinking about their expected utility from
 18 not buying, there's actually something going on or
 19 something that changes this failure rate and -- or
 20 distorts this failure rate, okay, and they're actually
 21 evaluating, you know, the relative value of buying
 22 versus not buying, okay?
 23 From the seller's side, essentially it's just
 24 monopoly pricing of the extended warranty, and this
 25 comes from Ellison's add-on pricing model, so I am not

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1 going to talk about it that much, given I don't have
 2 time.
 3 So the key challenge for identification is
 4 being able to -- so identification with respect to the
 5 consumers or for the buyers, the key challenge is how
 6 can you separate, you know, risk aversion -- standard
 7 risk aversion versus probability distortions, okay?
 8 So this graph shows, okay, on the Y axis, you have the
 9 distortion. Let's say the higher it is, the more
 10 distorted it is. So, for example, if the failure rate
 11 is 5 percent, the higher it is, you know, the more,
 12 you know, they're going to -- they're going to weight
 13 that 5 percent by, let's say, 7, then -- et cetera.
 14 Then on the X axis, you have risk aversion.
 15 So what these curves show you are iso
 16 willingness-to-pay curves, okay? So along the curve,
 17 okay, you have the same willingness to pay for a good
 18 that has repair cost p and some failure rate, Φ ,
 19 okay? And each point in this space is just a combi --
 20 is a person, so persons are characterized by a
 21 combination of r , the risk aversion, and how much they
 22 are distorting the probabilities, okay?
 23 And what this shows is that if you focus on,
 24 let's say, the dashed red curve, so that's the
 25 willingness to pay for a product with repair costs of,

<p style="text-align: right;">121</p> <p>1 say, pm-prime okay? We don't know -- suppose we know 2 that -- we see the product and we see what the 3 willingness to pay of people or of a person is, okay, 4 but we don't know whether it's a person who has high 5 risk aversion but they're not distorting probabilities 6 that much or is it the person with low risk aversion 7 but they are actually distorting probabilities a lot, 8 okay? So there is this identification problem in 9 terms of figuring out who this person is really is. 10 So the way we are going to do that in the paper 11 is we are going to look at, okay, another product, 12 okay, that has the same failure rate, but, okay, it 13 has a different loss or has a different repair cost, 14 because if -- so, first, for most utility functions, 15 if they desatisfy this single crossing property where 16 if you change the price, okay, even though these two 17 people have the same willingness to pay for, let's 18 say, product A, if we ask them, okay, how about 19 product B, what's your willingness to pay, we would 20 see that they can't have the same willingness to pay, 21 okay? 22 Specifically, more risk-averse buyers, okay, 23 will tend to increase, okay, if you give them another 24 product that has a higher loss, okay? They are going 25 to tend to value more the extended warranty relative</p>	<p style="text-align: right;">123</p> <p>1 sort of interesting aspect of the exercise. Okay, 2 let's take an experiment where you shut down the 3 distortions, okay, the probability distortions, so you 4 kind of like imagine that there's a way to force 5 people to evaluate the value of the warranty, thinking 6 that the failure rate is the actual failure rate, 7 okay? 8 When we do that, what's going to happen is, so, 9 we have -- when we're looking at quantities and 10 profits, okay, you see first in the quantities, so 11 this blue dash with circles is -- basically that's 12 (off mic), which is like monopoly and having biased 13 consumers. If you remove the bias, if you remove 14 distortions, okay, it's going to go to this monopoly 15 unbiased, so you maintain the market structure, okay, 16 you still can price as monopoly prices, but people are 17 no longer exhibiting the distortions. 18 What you are going to see is that quantity's 19 going to drop significantly, so about 80 percent, and 20 the consequence with respect to profit is actually 21 very large as well. So just if for some way you can 22 actually influence people's behavior in the sense that 23 they're not distorting probabilities, okay, it's going 24 to drastically change quantities and actually going to 25 lower profits by 90 percent, all right?</p>
<p style="text-align: right;">122</p> <p>1 to the other person, okay, if they're more 2 risk-averse, okay? So in a way the willingness to pay 3 increases faster for the more risk-averse guy relative 4 to the other guy, okay? So that's kind of idea of 5 identification. So we use that in the data, do 6 estimation, and what we find is the following. 7 This is a bit of a messy graph, and so the red 8 dashed line is 45 -- is the 45-degree line, basically 9 saying if your failure rate is 5 percent, then the way 10 you are going to evaluate that in your brain is also 11 going to be 5 percent, okay? What we estimate -- 12 let's focus on the red curve, okay, and the blue 13 dashed line, which is confidence interval. Basically, 14 one, there's a lot of probability distortion. So, for 15 example, a 5 percent failure rate is going to be 16 essentially equivalent to a 13 percent failure rate, 17 okay? All right, so that's one, okay? 18 So how do we judge, okay -- before that, 19 yeah -- and so what we find is probability distortions 20 actually drive consumer behavior. So when we estimate 21 these two -- so a model with probability distortions 22 and risk aversion, there's barely any risk aversion, 23 okay? That's what we get, okay? And everything is -- 24 seems to be explained more by probability distortion. 25 So let's look at the market itself. This is</p>	<p style="text-align: right;">124</p> <p>1 So it seems that it's really this probability 2 distortion story that is driving the high profits in 3 this market, okay, but it's important to understand 4 what exactly goes on in this probability distortion, 5 and right now it's as if we just, you know, have a 6 reduced-form explanation of why people are doing that, 7 and we saw that it has huge consequences on the 8 market, okay, but, you know, what else can we do, 9 okay? 10 Well, we need to understand the mechanism, so 11 here we're going to look at two, okay, drivers of 12 probability distortion. One is overestimation, 13 basically people just don't know what the failure rate 14 is, okay? And in this case, giving them information 15 may actually help them, and that might be the way to 16 shut down these distortions. 17 On the other hand, people may actually 18 overweight failure probabilities in the sense that 19 even if they knew what the failure rate is, they're 20 still not going to decide in that way, okay? They are 21 just going to artificially think, okay, it's a low 22 failure rate, but the way I'm trying to decide it, 23 because the imagery of a failure is so, you know, 24 affecting you, you are actually going to inflate, you 25 know, even though you have that information.</p>

125	<p>1 So in that sense it's not clear whether you</p> <p>2 want to intervene or whether you can even intervene</p> <p>3 and do something, but from a welfare point of view,</p> <p>4 you are actually not sure just to respect that type of</p> <p>5 consumer decision-making or, you know, you want to</p> <p>6 change it, okay? So it's not clear if overweighting</p> <p>7 is the mechanism.</p> <p>8 However, if it's overestimation, one, there's</p> <p>9 clear scope on what to do, you give them information,</p> <p>10 but at the same time, why they -- why they're doing</p> <p>11 that is because they're -- you know, it's actually a</p> <p>12 mistake, and, therefore, correcting it is</p> <p>13 welfare-enhancing both from the consumer and total</p> <p>14 welfare point of view, okay?</p> <p>15 So how do we get -- how do we get at the</p> <p>16 mechanism? So the other -- the first part was using</p> <p>17 data from Best Buy or whichever retailer it is, but to</p> <p>18 actually get the mechanism, you can't rely on just</p> <p>19 purchase behavior, okay, because you have to somehow,</p> <p>20 you know, have some intervention in figuring out,</p> <p>21 okay, what exactly is going on. So what we did is we</p> <p>22 ran an experiment, okay? So I don't have time to talk</p> <p>23 about the experiment, you know, but what we find is</p> <p>24 the following, okay?</p> <p>25 Willingness to pay significantly drops, okay,</p>	127	<p>1 provide information already, and then we look at --</p> <p>2 and we estimate how much are you still distorting</p> <p>3 probabilities versus is this really risk aversion that</p> <p>4 explains your willingness to pay. So here we say</p> <p>5 that, okay, probability distortions are minimal once</p> <p>6 you give them information, okay?</p> <p>7 So given that it's -- I guess I don't have much</p> <p>8 time, so I will just give a sort of punchline. So, in</p> <p>9 fact, this is a market where consumer policies are</p> <p>10 actually potentially more effective. And how is that?</p> <p>11 Well -- okay, so if you -- if you encourage</p> <p>12 competition, so suppose you have this price comparison</p> <p>13 website that everybody -- all of the retailers are</p> <p>14 going to price at marginal cost, okay, so prices of</p> <p>15 extended warranties are going to be very low, but if</p> <p>16 you don't correct the distortion or you don't give</p> <p>17 them information, then essentially you're encouraging</p> <p>18 more people to buy this useless product even if, in</p> <p>19 fact, if they knew better, they're actually not going</p> <p>20 to buy that product, okay?</p> <p>21 So in this case, okay, it might be</p> <p>22 counterproductive to actually do that, okay? And, in</p> <p>23 fact, it's more helpful -- more beneficial for</p> <p>24 consumer welfare to actually address the</p> <p>25 decision-making problem or mistake rather than</p>
126	<p>1 in the treatments where we give them information. So</p> <p>2 the experiment basically is that, okay, you're --</p> <p>3 you're -- we are told that there's this TV with a</p> <p>4 certain price, okay? One treatment asks you how much</p> <p>5 are you willing to pay, and then they -- we also ask</p> <p>6 what's the likelihood -- what do you think is the</p> <p>7 likelihood that this TV is going to break down.</p> <p>8 There's one treatment where we reverse the order. And</p> <p>9 then there's this -- basically the main treatment,</p> <p>10 which is to actually tell them before -- you tell them</p> <p>11 that it's 5 percent and then, you know, you ask their</p> <p>12 willingness to pay.</p> <p>13 So we see that just focusing on the means, but</p> <p>14 everything is reflected in distributions as well, the</p> <p>15 one where you give information, the rightmost column,</p> <p>16 okay, there's a significant drop in the willingness to</p> <p>17 pay once you say it's 5 percent, okay? All right? So</p> <p>18 I am going to skip this, okay?</p> <p>19 This basically says that, okay, what else is</p> <p>20 left after you give them information? So we use --</p> <p>21 what's the nice thing about this project is that we</p> <p>22 actually used that identification strategy to design</p> <p>23 an experiment to precisely get at what we want, okay?</p> <p>24 So to be able to separately estimate these two things.</p> <p>25 So this -- we have a second experiment where we</p>	128	<p>1 encouraging competition, but, of course, if you have</p> <p>2 both, then that's the ideal scenario.</p> <p>3 Okay. Sorry for -- okay, thank you.</p> <p>4 (Applause.)</p> <p>5 MR. WILSON: Thanks very much. Our discussant</p> <p>6 will be Ginger Jin of the University of Maryland.</p> <p>7 MS. JIN: Well, thank you so much for having</p> <p>8 me. It's great to be here.</p> <p>9 Okay, let me start by saying that I loved the</p> <p>10 paper. About ten years ago, I tried to persuade my</p> <p>11 student to look at extended warranty given its</p> <p>12 similarly high and abnormal profit; however, I was not</p> <p>13 successful at all. So this paper really satisfies my</p> <p>14 intellectual curiosity in a long way by sharpening the</p> <p>15 question in a policy-relevant context. This also</p> <p>16 drills down into the mechanisms even after we know</p> <p>17 we're in the box of consumer misperception.</p> <p>18 It also provides a rare case that we can</p> <p>19 compare competition policy with consumer information</p> <p>20 policy to see -- kind of run a horse race between the</p> <p>21 two and see which one will be more effective in</p> <p>22 addressing the market issues. I really appreciate the</p> <p>23 creative use of (indiscernible) methodology, both the</p> <p>24 structural modeling of a very impressive data set as</p> <p>25 well as the complementary experiment they run to get</p>

129	<p>1 into the key issues. It also provides a good 2 combination of the empirical facts as well as the 3 theory that's well known in the literature. 4 So just to summarize the main findings, the 5 first one is the high takeup of extended warranty is 6 mostly driven by consumer misperception. I'm quite 7 convinced by that conclusion. Also, they find that a 8 consumer perception is mostly driven by lack of 9 accurate information and in the failure probability 10 versus some alternative explanations. And the third 11 one is sort of a surprise, but I really feel it's very 12 sensible, where they find that fixing the 13 misinformation is much more effective than fixing 14 monopoly power, and fixing monopoly power alone 15 actually would reduce consumer welfare. This is 16 really speaking to the intersection between antitrust 17 policy and consumer policy that's sort of emphasized 18 the point that we not only should think of them as 19 substitutes, and sometimes they would have these 20 sophisticated interaction effects that actually we 21 cannot think of each one in its isolation. 22 So I have a few comments and hopefully can help 23 improve the paper. The first one is about product 24 substitution. If I understand the model correctly, 25 the model is sort of thinking, okay, the consumer</p>	131	<p>1 That's by requiring the firms to post the price not 2 only on the product, but also on the extended warranty 3 at the same time. So if we think of the products as a 4 bundle, then it's sort of different from the structure 5 adopted by this paper. So I think it will be good for 6 the paper to clarify at least what we're missing by 7 not focusing on the product substitution margin. 8 Relatedly, my second comment is about price 9 endogeneity. So let me see if I understand the 10 identification correctly. They basically assume the 11 perceived probability as a function of the real 12 probability, plus some random variation, okay? And 13 then they look at a pair of products that have the 14 same actual failure rate but different prices, okay? 15 And then they are using the moment condition that the 16 difference between those two products in terms of 17 perceived probability is independent of the price we 18 observe for the product, as well as for the extended 19 warranty. 20 So this sort of requires the price to be 21 exogenous at both levels; however, I can think of at 22 least a few stories that could violate this 23 assumption. For example, the store may set the price 24 according to their perception of the consumer 25 perception of failure rate. So if, let's say, two TV</p>
130	<p>1 already decided to buy a certain product. It's just a 2 question of whether you want to buy the extended 3 warranty or not. So in the data, you see individual i 4 buying product j with and without extended warranty, 5 and then you observe another consumer buying probably 6 another product with and without extended warranty. 7 However, my -- at least my consumer experience 8 is not that I already paid for that TV before I 9 consider whether I'm buying extended warranty or not; 10 rather, I probably have settled down on a model, and 11 then the salesman would tell me the extended warranty, 12 and then I may say, okay, that's a good deal or not a 13 good deal, and then I probably would ask, okay, what's 14 a similar extended warranty price on a substitutable 15 TV. 16 So in that sense, the model could be sort of -- 17 the alternative model could be that the consumer eyes, 18 looking at multiple products, for each one of them 19 will have extended warranty or not warranty situation. 20 So I wondered what do we miss by ignoring this 21 product-level substitution and only focus on this 22 add-on part? 23 The policy proposed by UK seems to push the 24 market or at least push the consumers to think about 25 the product and extended warranty as a bundle, right?</p>	132	<p>1 models have the same actual failure probability, but 2 one is a well known brand and the other is not so well 3 known, maybe new and emerging, then consumers may have 4 different perception on the actual failure rate, and I 5 would imagine that the store may want to price them 6 differently, depending on the consumer reputation 7 about those two brands. So that's story one. 8 And story two is consumers probably really 9 don't know what's the probability to think about when 10 they buy a TV or a consumer electronics; however, they 11 may use the extended warranty price to try to 12 reverse-engineer the probability, at least I did that 13 when I was a consumer. I'm not sure how successful I 14 was, but if I try to say I look at this extended 15 warranty price, which is 22 percent of the actual 16 product, does that make me think about, oh, maybe the 17 actual probability is close to 22 percent or I compare 18 that with my prior and then decide what to buy? If 19 that's the case, then this price of extended warranty 20 would have the signaling feature that could make this 21 independent assumption violated. 22 The paper is sort of using, at least in the 23 main specification, using the maximum price of the 24 product as the price, so it's probably not as severe 25 as I'm thinking as the actual price in that</p>

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1 transaction for the product; however, I don't know to
2 what extent that sort of alleviate the endogeneity
3 problem.

4 Okay, I really love the experiments. They have
5 run three experiments. One asks consumers to report
6 their willingness to pay first. The second is -- asks
7 them to report their estimated likelihood of failure
8 first. And the third one is providing the information
9 first. So I would suggest to run a fourth experiment
10 to sort of confirm or probably refute my story that
11 the price might be a signal of extended warranty if
12 you sort of present the price of the extended warranty
13 first and then -- just to see how the subject's going
14 to buy the -- the product or not buy the product, or
15 you can even sort of have a middle question, asking
16 them what's the likelihood given the price they face
17 from the store.

18 So I have other comments, and they are probably
19 mostly data questions. For example, how do the price
20 vary with each other? I don't know whether the store
21 have kind of constant rate -- constant price ratio
22 between the product price and extended warranty price,
23 or that actually vary across products or over time or
24 across different locations of the stores. And I don't
25 know -- probably given that you don't know the

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1 identity of the store, you probably cannot speak much
2 to whether the store have more sort of salesmen
3 devoted to the categories that would generate more
4 profit in this add-on product.

5 In the experiment, you have to look at the
6 experiment of likelihood first, that's asking them to
7 predict the failure rate, and then report their
8 willingness to pay, and you sort of interpreted this
9 as a kind of a reminder effect, that you remind the
10 consumers to think about probability, which sort of
11 put them in more disciplined way to talk about their
12 willingness to pay.

13 I guess probably a related story could be that
14 you forced them to be sort of self-consistent. If I
15 have reported the probability to be 5 percent, it will
16 be very hard for me to justify my willingness to pay
17 to be 20 percent of the actual price. So I wonder
18 whether that could be an alternative explanation.

19 And lastly, I was fascinated by the fact that
20 the -- what do you call it -- attachment rate, that's
21 the takeup rate of extended warranty, vary a lot by
22 income, and actually income is the only factor that
23 seems important to determine who is buying this
24 extended warranty, and the low-income group have a
25 much higher attachment rate than the low-income group,

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1 so this introduce very interesting question. For
2 example, are low-income households more susceptible to
3 this misperception and whether the firms actually try
4 to take advantage of that differential misperception,
5 for example?

6 Okay, I guess that's basically my comments. I
7 really loved the paper and hope to see the next
8 version. Thank you.

9 (Applause.)

10 MR. WILSON: Thanks very much. I think we have
11 got time for a couple of questions.

12 AUDIENCE MEMBER: I enjoyed the paper, too.
13 Following up on Ginger's comment, I know with extended
14 warranties it's sometimes argued that the
15 decision-making of somebody who's credit-constrained
16 will be different from somebody who's not. So can you
17 speak to that?

18 MR. ABITO: In terms of credit constraints,
19 yeah, we didn't include that in the model, but what we
20 can say a little bit -- and this is actually answering
21 also Ginger's discussion -- is we actually
22 estimated -- or it's not in the paper, but we
23 estimated the model for households which are above the
24 median category in terms of income and then for
25 low-income category households. So to the extent that

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1 that somehow related to credit constraints, then --
2 but I think with credit constraints actually it
3 might -- it might be a little bit more complicated in
4 terms of modeling.

5 But just to say something about heterogeneity
6 in both risk aversion and probability distortion is we
7 do, in fact, see that low-income households are more
8 distorted in terms of the probability distortion.
9 Yeah, yes.

10 MR. SWEETING: Andrew Sweeting from the
11 University of Maryland. So in your model you had
12 everyone having a homogenous kind of distortion to
13 their probabilities, and I guess to me this struck me
14 as an area where you might think in terms of a kind of
15 sophisticated naive model, where when you are thinking
16 about kind of the welfare implications, probably the
17 existence of the naives is potentially going to be
18 reducing the retail margin on TVs that charge the
19 sophisticates.

20 And I actually just wondered, were there
21 different policy implications that might emerge in
22 that kind of setup as compared with the framework that
23 you're using?

24 MR. ABITO: That's a great question. So one
25 way to also -- so the model we adopt is Ellison's

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1 add-on pricing model, which these part one
2 specifications -- one tweak of the model is you have
3 sophisticated and naive consumers. And actually, I
4 would like to answer this question echoing back to one
5 of the things Ginger mentioned, is, okay, what if we
6 think about a model where the consumer's thinking
7 about the TV and the bun -- the TV and the warranty as
8 a bundle.

9 So in the standard -- in the add-on pricing --
10 well, in Ellison's model, if that's the case, then
11 extended warranty prices are still going to be set at
12 monopoly prices, but that's going to be competed away.
13 So it's actually not profitable for retailers to do
14 that, okay?

15 On the other hand, if you have switching costs
16 and unobservability of price, then you are going to
17 have the same -- basically you will have monopoly
18 pricing of the extended warranty, but at the same
19 time, it's not going to affect the pricing of the main
20 good. So in a way that -- it actually can -- or it
21 reduces the incentive of firms to decrease the price
22 of the main good to attract people to buy the extended
23 warranty.

24 And so in order for that to happen, you
25 actually have to have the right mix of, in this case,

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1 sophisticated and naive. If you have too many
2 sophisticated guys, then maybe, you know -- so it --
3 the reason why you don't want to reduce the price of
4 the main good to attract people to buy the extended
5 warranty is that, okay, you are going to mostly
6 attract the cheapskates or the naive ones -- or the
7 sophisticated ones, and, you know, they are going to
8 take advantage of the lower price but essentially not
9 buy the warranty. So, yeah, it really -- then maybe
10 competition policy has a bigger role, okay?

11 MR. SWEETING: Thank you.

12 MR. BRUESTLE: Hi. Steven Bruestle, Federal
13 Maritime Commission.

14 Is there more probability distortion for newer
15 products? For example, there could be less word of
16 mouth or experience for newer products.

17 MR. ABITO: Ah, we didn't check that. That's a
18 great question.

19 MR. BRUESTLE: It could be a really good
20 natural experiment, too. It could be a good proxy.

21 MR. ABITO: Yeah. One thing that we kind of
22 did -- we did that kind of addresses that is less
23 about the product but more about the consumer. So we
24 have -- I think I did answer this question. We do
25 actually estimate this with heterogenous preferences,

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1 okay, and one thing about -- one form of heterogeneity
2 that we looked at with consumers is that we have this
3 measure of experience, okay, with a good, so
4 essentially you can say, okay, new products, less
5 experience, and you can kind of map that setting into
6 what we did. So we obviously found that more
7 experienced guys almost not have probability
8 distortions.

9 MR. BRUESTLE: Okay.

10 MR. ABITO: So in the sense that, okay, newer
11 goods might have stronger probability distortion. So,
12 yeah, yes.

13 MR. BRUESTLE: Thank you.

14 MR. RASMUSEN: Actually, kind of along the same
15 lines, do you know if these products have gotten more
16 reliable over the years in a close enough time,
17 because that would explain misperceptions. I remember
18 when I was a boy, we actually had a TV repairman come
19 to our house to change tubes, and disk drives used to
20 fail a lot, hard drives, and I don't hear about that
21 nowadays.

22 MR. ABITO: Yeah. So definitely failure rates,
23 for example, for TVs have gone down now. It's about 5
24 percent. I am not sure I got your second question,
25 given --

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1 MR. RASMUSEN: Well, so that's since 1970,
2 maybe. Since 2000, have they gone down?

3 MR. ABITO: Well, even just comparing 2004 and
4 now, the -- the -- so most of the repairs here is
5 something with the screen, and the technology for
6 developing more reliable screens actually has
7 improved, so definitely failure rates -- so that's
8 actually what's funny -- or not funny, but the failure
9 rates have gone down, but then the prices are still
10 that high. Yeah, so -- yeah. Of the warranty I mean.

11 AUDIENCE MEMBER: (Off mic.)

12 MR. ABITO: Have less distortion, yeah, yeah.

13 I mean, they know how to handle the products, and they
14 kind of see that, you know, these are not -- not --

15 AUDIENCE MEMBER: (Off mic.) More experienced
16 guys would be more distorted if there's higher
17 demand -- higher probability (off mic).

18 MR. ABITO: All right.

19 MR. ROSENBAUM: Okay, great. Thank you.

20 MR. ABITO: All right, thanks.

21 (Applause.)

22 MR. ROSENBAUM: Thank you very much.

23 (End of session.)

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25

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142	<p>1 really high-skill professions, but you also have 2 occupational licensing of medium-skill professions, 3 like electricians, plumbers, or painters, and then 4 even low-skill professions or at least low-risk 5 professions, such as hair braiders. 6 So to give you an example of one profession 7 that we're going to study, interior painting, so the 8 map of the U.S. shows the states in yellow, those are 9 the ones where the states have specific occupational 10 licensing regulation regarding painting. Furthermore, 11 the states in white, they don't have a statewide 12 regulation, but individual cities might have a 13 regulation. So in Texas, San Antonio would have a 14 regulation about interior painting. 15 And then across the states that do regulate 16 occupational licensing, there's a lot of variation. 17 So for example in Nevada, you have over a thousand 18 dollars' worth of fees. You have to have four years 19 of experience, which is oftentimes apprenticeship. 20 You have two exams. And by the way, the pass rates on 21 these exams are actually not very high. We were able 22 to check that in a few cases. And then one caveat I 23 should point out is that there are oftentimes cutoffs 24 in these occupational licensing laws. So if the job 25 exceeds, let's say, a thousand dollars, then you need</p>	144	<p>1 actually serve as a substitute for licenses. 2 So in this paper we're going to ask two 3 research questions. Do customers care about 4 occupational licensing status on this online platform? 5 And we find that, if anything, they dislike 6 occupational licenses, and reviews matter a lot more 7 for the consumer choices. And then secondly, we study 8 a more aggregate outcome, which are equilibrium 9 outcomes in terms of the match rates, the prices, and 10 the ratings, as they vary by the stringency of a 11 licensing regime across states and occupations, and we 12 find that more stringent licensing regimes lead to 13 less competition and higher prices on average, but no 14 detectable effects on customer satisfaction, so -- and 15 we don't find strong evidence of benefits of 16 occupational licensing. 17 Okay, so the rest of the talk is going to be in 18 three parts. First of all, I'll describe the setting 19 and some descriptive statistics. Secondly, I'll 20 describe the individual choices. And thirdly, the 21 aggregate outcomes. 22 Okay. So the setting is an online platform for 23 home improvement services. It has national reach. It 24 has millions of transactions that happen on it. And 25 I'd like to say that home improvement isn't just,</p>

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1 like, an interesting test case for occupational
 2 licensing. It's an important profession. Broadly
 3 construed, there are over 5.3 million workers in the
 4 construction industry, and they -- these are the types
 5 of jobs that are unlikely to go away any time soon.
 6 So the way the platform works is that a
 7 customer will have a local service need, so maybe I'm
 8 looking for a painter in D.C. I'm going to Google
 9 "painters near me" or "painters in D.C.," and this
 10 platform will be one of the top search results. The
 11 customer is going to enter the platform, and they are
 12 going to be asked to submit a detailed job request.
 13 That might say, how big is your place? Where is it
 14 located? What type of paint would you like to use?
 15 How quickly would you like this done? And other
 16 things you might think about.
 17 Once the customer submits this, pros are going
 18 to pay to submit a bid on a particular request for a
 19 job. So that's the business model of the platform.
 20 The pros are paying to get the lead. And there is a
 21 maximum amount of pros that can submit bids for a
 22 given customer. And then after that, the customer can
 23 choose to hire one of the pros.
 24 So here's a stylized version of the profiles
 25 that each pro might have. So we have Interiors by

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1 Chiara Farronato. She has one review. In contrast,
 2 Fradkin International Design have ten reviews, but
 3 there are three stars average rating, and I'm also
 4 licensed to be an interior designer. So that's the
 5 important part, is that when the platform has verified
 6 your license, that license is displayed in your
 7 profile information.
 8 So how does the platform verify these licenses?
 9 So, first of all, the pro must submit the license to
 10 the platform, and then once the platform receives the
 11 license, they're going to take some amount of time to
 12 verify it, and the way that they would do so is they
 13 would go to the appropriate state-level website, so
 14 let's say the Licensing Board of California, and they
 15 would go look for that ID number and make sure that it
 16 matches up with the pro. And a key for us is that the
 17 amount of time it takes a platform to verify the
 18 license is quasi-random.
 19 So what are the types of jobs that are
 20 available on the platform? Lots of contractors, so
 21 general contractors, HVAC contractors, painting
 22 contractors, and so on and so forth; plumbers,
 23 electricians, home inspectors, pest control and
 24 pesticide applicators. So you should be thinking
 25 about these types of jobs.

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1 In terms of -- oh, I guess old slides. In
 2 terms of the summary statistics, we see that at least
 3 in our sample of quotes about 12 percent of the quotes
 4 are by a pro that has a license validated at that
 5 time, and 14 percent by a pro that has submitted a
 6 license to the platform at that time. The typical
 7 quote has four reviews and a 4.9 pro rating. So as
 8 with other online platforms, the ratings are typically
 9 skewed towards five stars. It's the -- it's one out
 10 of five stars -- sorry, or it's out of five stars that
 11 the rating is.
 12 And then conditional on hire, we see that hires
 13 tend to have more reviews and lower prices relative to
 14 the quotes, which is, I guess, not very surprising.
 15 Importantly, since we're going to be studying
 16 both reviews and licenses, we want to see, do licenses
 17 predict the quality of the transaction as measured by
 18 the rating that a pro receives from a customer? And
 19 so what we see is that just the raw correlation, this
 20 is a small positive relationship between whether you
 21 have the license validated at the time that you did
 22 the job and the rating that the customer gives you
 23 once you did that job.
 24 But once we control for whether you've
 25 submitted the license, it seems that that's what's

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1 soaking up most of that correlation, and this holds
 2 when we add more controls.
 3 Another thing we can do is, even before you
 4 submitted the license, you were probably already a
 5 licensed pro; you just hadn't gotten around to
 6 submitting the license to the platform. So we control
 7 for whether you've ever been licensed on the platform,
 8 and that soaks up a little bit more of the variation.
 9 And then, finally, the last column is going to
 10 have pro fixed effects, and we don't see any change in
 11 the types of ratings that you get as you get validated
 12 on the platform. So I would view this as generally --
 13 there isn't strong evidence that licenses on the
 14 platform are predicting five-star ratings here.
 15 So one thing I mentioned previously was pros
 16 might not need a license for certain types of jobs.
 17 So here we made two plots for California, one for
 18 general contractors and one for painters, where
 19 California's law is that if it's over \$500, you need a
 20 license, and so you can see that both pros that have
 21 gotten licensed on the platform and pros that haven't
 22 gotten licensed on the platform oftentimes bid more
 23 than the \$500 limit. So this could mean that they are
 24 really licensed, they just haven't told the platform,
 25 or it could mean that maybe they're not paying

149	<p>1 attention to licensing laws. We don't know. Okay.</p> <p>2 So that's a description of the setting.</p> <p>3 Now getting to the study of the individual</p> <p>4 choices, so the basic type of regression we would like</p> <p>5 to estimate is the outcome variable is whether the</p> <p>6 customer hired a particular pro as a function of the</p> <p>7 pro characteristics and the bid characteristics, and</p> <p>8 the variables that we're interested in are licensed,</p> <p>9 price, number of reviews, and the average rating that</p> <p>10 you get. And just to kind of give you a sense, like,</p> <p>11 every pro is going to bid a particular dollar -- fixed</p> <p>12 dollar amount, and it might have some text associated</p> <p>13 with the bid as well.</p> <p>14 In terms of the identification strategy, where</p> <p>15 you need a separate identification strategy for all</p> <p>16 these variables. So for the licensing variable, we're</p> <p>17 going to use the fact that there is this quasi-random</p> <p>18 amount of time that it takes for the platform to</p> <p>19 verify a submitted license as being verified and to</p> <p>20 display it on the site. So we're just going to have a</p> <p>21 control for whether the pro has submitted a license at</p> <p>22 the time and whether the pro's license has been</p> <p>23 verified by the platform.</p> <p>24 Secondly, our instrument for price is going to</p> <p>25 be the distance between the pro and the customer. So</p>	151	<p>1 where the timing is relative to the time when the</p> <p>2 license was validated. So we don't see a</p> <p>3 statistically significant effect at the time of</p> <p>4 validation in the hire rate, and the variation in</p> <p>5 these coefficients is very small. So there doesn't</p> <p>6 seem to be much evidence that customers are paying</p> <p>7 attention to the validation of the license.</p> <p>8 You might say, well, maybe the pros are</p> <p>9 changing their behavior in response to getting the</p> <p>10 license validated, and we don't see evidence of that</p> <p>11 either. This is the same regression where the outcome</p> <p>12 variable is price.</p> <p>13 Okay. So now getting to that full</p> <p>14 specification where we have license, ratings, and</p> <p>15 reviews, I'll go through each of the specifications in</p> <p>16 order. So these are the results from the OLS, and the</p> <p>17 column I've highlighted includes professional fixed</p> <p>18 effects and request fixed effects. So we don't see an</p> <p>19 effect of licensing in the specification. We see a</p> <p>20 positive effect of average ratings, a negative effect</p> <p>21 of the number of reviews and of the price. So we need</p> <p>22 some instruments here.</p> <p>23 So the next column is going to add an</p> <p>24 instrument for price, and we see that the coefficient</p> <p>25 on price becomes much more negative, exactly as we</p>
150	<p>1 the customer presumably doesn't care where the pro is</p> <p>2 located, but it takes more time for the pro to get to</p> <p>3 the customer, and that should be a cost shifter there.</p> <p>4 And then, lastly, for the reviews and the</p> <p>5 average rating, we're going to use the characteristics</p> <p>6 of the prior reviewers of that particular pro. So if</p> <p>7 the prior reviewers of that pro tended to be harsh,</p> <p>8 that they reviewed other pros with lower ratings, that</p> <p>9 should shift around the ratings of a given pro. And</p> <p>10 similarly, for the propensity of the customers of the</p> <p>11 prior professional -- of the prior -- for the</p> <p>12 customers of the pro before this given quote, if they</p> <p>13 were more likely to submit reviews, then that should</p> <p>14 increase the number of reviews of the pro.</p> <p>15 Okay. So before getting to that full</p> <p>16 specification, we're going to do an event study</p> <p>17 analysis. So here we just include professional fixed</p> <p>18 effects and request fixed effects, and the licenses</p> <p>19 that we are going to use for this are going to be</p> <p>20 occupation-specific licenses, so we are going to throw</p> <p>21 out business licenses and inappropriate licenses. So</p> <p>22 like some of these might have, like, an accountant</p> <p>23 license, but they're not doing the accounting job, so</p> <p>24 we are not going to include that.</p> <p>25 So here are the results of this regression,</p>	152	<p>1 would expect. And then the last column is going to</p> <p>2 add our reviews for ratings, and in that specification</p> <p>3 what we see is a small negative effect of license</p> <p>4 verified on consumer choices and positive effects of</p> <p>5 having higher ratings and having more reviews and a</p> <p>6 negative effect of price. So in terms of relative</p> <p>7 magnitudes, the license verified doesn't seem very</p> <p>8 important to these other variables.</p> <p>9 We can also look at the same type of regression</p> <p>10 where the outcome is going to be whether the customer</p> <p>11 viewed a quote. So the customer gets a list of</p> <p>12 quotes, and they don't have to view all of them. So</p> <p>13 we kind of see more views than hires. And when</p> <p>14 looking at this outcome variable, we see very similar</p> <p>15 results in the sense that people are going to be more</p> <p>16 likely to view a quote from a pro if that pro has more</p> <p>17 ratings, more reviews, less likely if it's a higher</p> <p>18 price, and having a license verified actually</p> <p>19 decreases the view rate.</p> <p>20 One thing that we thought might be worth</p> <p>21 looking at is interactions of license verified with</p> <p>22 review-rated variables, but we don't see any</p> <p>23 consistent patterns here. So I am not going to</p> <p>24 discuss this any further.</p> <p>25 Okay. So what does this mean? Consumers might</p>

153	<p>1 not pay much attention to the licensing for various</p> <p>2 reasons. One might be they just don't really know</p> <p>3 what a license is doing, so they don't care. They</p> <p>4 might not pay attention because they rationally know</p> <p>5 that licenses don't actually affect quality in this</p> <p>6 market, or maybe they just assume that everyone is</p> <p>7 licensed and that's why they don't pay attention.</p> <p>8 We don't really have much to say about which of</p> <p>9 these stories is true, although manual inspection of</p> <p>10 pros suggested that it was very hard to find licenses</p> <p>11 for some of them, and part of that is just that the</p> <p>12 name under which a pro might have registered their</p> <p>13 license at could have been different from the one that</p> <p>14 we observed on the platform, but it could be that</p> <p>15 they're actually not licensed.</p> <p>16 All right. So now moving on to the aggregate</p> <p>17 outcomes, so what we want to know is how licensing</p> <p>18 stringency is going to affect outcomes on this</p> <p>19 platform in terms of competition, prices, and quality,</p> <p>20 and the identification we're going to use is going to</p> <p>21 be across zip code, across licensing stringency. So</p> <p>22 think about painters and electricians in California</p> <p>23 versus painters and electricians in Nevada. If Nevada</p> <p>24 happens to have more stringent licensing for painters,</p> <p>25 then we should -- then our regression is going to pick</p>	155	<p>1 observe these variables, we conduct a PCA analysis to</p> <p>2 create a one-dimensional score of licensing</p> <p>3 stringency, and we're going to exclude in these</p> <p>4 regressions states that don't have a statewide</p> <p>5 occupational licensing regulation for a given</p> <p>6 profession.</p> <p>7 So what are the factors that are correlated</p> <p>8 with this dimension we've identified? They're going</p> <p>9 to be fees, exams, minimum grade, minimum age,</p> <p>10 education and credits but not in years, and then</p> <p>11 experience in terms of years. So generally most of</p> <p>12 the factors are positively loaded. Most of the</p> <p>13 variables are positively loaded in this factor.</p> <p>14 Okay. So here's the standard regression that</p> <p>15 we have. So we see that the number of quotes is</p> <p>16 negatively associated with licensing stringency. The</p> <p>17 prices are positively associated with licensing</p> <p>18 stringency. Then there's no effect on star ratings or</p> <p>19 whether the customer comes back to the platform.</p> <p>20 Now, some of these estimates are a bit noisy,</p> <p>21 and you might also be saying, well, there's a -- kind</p> <p>22 of one thing that can be very different between</p> <p>23 different zip codes and different states. Maybe the</p> <p>24 types of painting jobs that one does in Nevada might</p> <p>25 be different from Massachusetts or North Carolina. So</p>
154	<p>1 up the effect of that relatively more stringent</p> <p>2 licensing on painters in Nevada compared to</p> <p>3 California.</p> <p>4 So the regression that we're going to estimate</p> <p>5 is the following, where the outcome variables are</p> <p>6 going to be the number of quotes that a given task</p> <p>7 receives, the quoted prices, whether there was a match</p> <p>8 or not, what the price of the winning quote was, and</p> <p>9 then outcome variables such as the star rating and</p> <p>10 whether the customer comes back to the platform, which</p> <p>11 are measures of quality. And the observations are</p> <p>12 going to be at the request, zip code category, and</p> <p>13 month/year level, where importantly we're interested</p> <p>14 in the coefficient on licensing stringency.</p> <p>15 So that actually raises the next question. How</p> <p>16 does one measure licensing stringency? So we start</p> <p>17 with a database that the Institute for Justice has</p> <p>18 compiled called Licensed to Work, which includes, for</p> <p>19 a wide variety of professions, the fees that you need</p> <p>20 to get licensed and exams, the minimum grade and age,</p> <p>21 education and experience.</p> <p>22 We've also -- and this is not in progress, this</p> <p>23 is in the data -- we've also compiled our own</p> <p>24 information about general contractors, electricians,</p> <p>25 and plumbers to augment that data. And then once we</p>	156	<p>1 what we do next is we are able to control for these</p> <p>2 very detailed requests, characteristics.</p> <p>3 Do you have like a 2000-square foot house? Do</p> <p>4 you need this type of paint or that type of paint?</p> <p>5 For each separate profession, using the double ML</p> <p>6 technique of Chernozhukov, et al. So the basic idea</p> <p>7 behind that is you split your sample, and for one-half</p> <p>8 of your sample, you estimate a machine-learning model</p> <p>9 that predicts both the outcome and the treatment,</p> <p>10 which in our case is stringency, as a function of all</p> <p>11 these detailed task-level characteristics, where we</p> <p>12 use a lasso estimator.</p> <p>13 And then on the other sample, you estimate the</p> <p>14 model that you're interested in, which is the outcome</p> <p>15 variable on the residualized licensing stringency, and</p> <p>16 we get the following results, which are now precise</p> <p>17 but actually very similar in magnitude to the ones</p> <p>18 that we saw on the previous slide. So having more</p> <p>19 stringent licenses associated with fewer quotes,</p> <p>20 higher prices, lower match probability, and no</p> <p>21 difference in terms of customer satisfaction.</p> <p>22 We also tried to do some heterogeneity</p> <p>23 analysis, where each of these is a profession, and</p> <p>24 we're kind of -- and most of the heterogeneity points</p> <p>25 in the same direction as the regression that pools all</p>

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1 the categories together, and we're -- and we aren't
 2 able to, once again, detect any effect, even at a
 3 profession level, on star ratings or whether the
 4 customer returns to the platforms, which are quality
 5 measures of the professional.
 6 Okay. So what have we learned from this? So
 7 kind of a narrow interpretation of this is that we've
 8 learned the effect of licensing for digitally
 9 initiated transactions, which might be a very small
 10 subset of all transactions. Kind of a broad
 11 interpretation is that we've learned something about
 12 the effect of licensing both online and offline, and
 13 that would be true if the service providers online are
 14 not systematically different from the service
 15 providers offline, and if consumers spend the same
 16 effort verifying licenses online and offline, which
 17 may or may not be reasonable depending on the
 18 particular job that we're thinking about.
 19 So in conclusion, how do licenses and reviews
 20 affect customer choices? We find that reviews matter
 21 much more than licenses. And how do equilibrium
 22 outcomes vary with licensing stringency? We see that
 23 more stringent licenses are associated with less
 24 competition and higher prices, but no detectable
 25 effect on satisfaction. And lastly, it's still very

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1 much a work in progress, so I'm looking forward to
 2 your comments.
 3 (Applause.)
 4 MR. ROSENBAUM: And Judy Chevalier from Yale
 5 will be the discussant.
 6 MS. CHEVALIER: I had a little miscommunication
 7 about my slides, so I am going to use Andrey's, and
 8 his are better than mine were going to be anyway, so
 9 we're good.
 10 Okay, great. Thanks. So let me thank the
 11 organizers for inviting me to discuss this paper.
 12 I've done work in the past on both occupational
 13 licensing and review platforms, and so I'm somewhat
 14 jealous that I didn't think, you know, to put those
 15 two things together.
 16 And, you know, when I think about this paper,
 17 what I think the contribution is, you know, when we
 18 are -- we're living in a world with more review
 19 platforms than we have ever had before, which means
 20 that consumers are observing more things about
 21 providers in all kinds of spheres than they were
 22 before, and even if we thought the occupational
 23 licensing regime was optimal at some point in time --
 24 which, by the way, I'm pretty sure we don't -- but
 25 even if we thought that, you know, with more consumer

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1 information, presumably the optimal occupational
 2 licensing regime would change, and so this paper
 3 explores that in I think a very interesting and
 4 persuasive way.
 5 Okay. So when I look at occupational
 6 licensing, the authors emphasize this motivation, and,
 7 you know, we're at the FTC Bureau of Economic Analysis
 8 where the charge is competition and consumer
 9 protection, and the authors focus on competition and
 10 consumer protection, and many of us are IO economists,
 11 so that is the place to focus, but I do want to back
 12 out a little bit from the motivation here that the
 13 authors provide and just remind ourselves what other
 14 areas of economics tell us about occupational
 15 licensing, right?
 16 So what are some concerns about occupational
 17 licensing? Well, one thing about occupational
 18 licensing is that it impedes economic adjustment
 19 because it impedes worker mobility, right? So there
 20 are jobs -- if job opportunities are declining in
 21 Michigan and rising in Wisconsin, we would like
 22 workers to move from Michigan to Wisconsin, and
 23 occupational licensing imposes a barrier on that kind
 24 of mobility.
 25 Second, occupational licensing imposes a

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1 barrier on economic mobility, right? So we have --
 2 the classic example would be, you know, we have a new
 3 immigrant who's very skilled at hair-braiding, and,
 4 you know, would be a great hair-braider if only she
 5 could meet the licensing requirements, all right? And
 6 so the ability to that worker to match to the best job
 7 that matches her skills is actually impeded by
 8 occupational licensing.
 9 And I remind us of this because usually when we
 10 do these kind of welfare things in IO, we're kind of
 11 wanting to ask ourselves, you know, do these pluses
 12 outweigh these minuses, right? Does the consumer
 13 protection outweigh the competition and pricing
 14 issues? But here I've just told you two labor market
 15 things that are just unambiguously bad, right? So the
 16 consumer protection part better kind of hit the ball
 17 out of the park if we're going to tolerate a lot of
 18 really strict occupational licensing, right? So just
 19 a framing to think about occupational licensing in
 20 this context.
 21 Okay, so the authors have two research
 22 questions, and I want to turn a little bit to some
 23 critiques of each, and, you know, let me say I'm going
 24 to do the usual discussant thing of nit-picking a
 25 little bit, though on net, I am very skeptical of many

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1 of these state occupational licenses, and I don't want
 2 that message to get lost in my nit-picking here,
 3 because I think in general I pretty much believe the
 4 results that the authors have come up with.
 5 Okay. So the first result is that consumers on
 6 this site are not much impacted in their choice of
 7 pros and in the reviews that they ultimately leave by
 8 whether or not the pros have verified licenses on the
 9 site. Now, one thing I would like to maybe spend a
 10 little more time on than Andrey did is this issue of
 11 consumer beliefs when there isn't a license posted on
 12 the site, and, you know, Andrey said forthrightly that
 13 it's not clear what the consumer believes in that
 14 circumstance, but what I want to point out is what the
 15 consumer believes is probably heterogenous across
 16 these various occupation types.
 17 So, for example, when I think about an
 18 electrician or a plumber, you know, if I see something
 19 advertised as Fradkin Plumbing Company or Fradkin
 20 Electrical Company, I have a strong prior that
 21 electricians and plumbers are regulated, and they're
 22 regulated pretty much everywhere. In contrast,
 23 painters, as we saw in the picture, are regulated in
 24 some places, not regulated in some places, regulated
 25 in some circumstances, not regulated in some

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1 circumstances. My guess is the typical consumer, when
 2 going to the site, has a strong prior that the
 3 electricians and the plumbers are regulated and have
 4 occupational licenses, and maybe has a much more
 5 diffuse prior about the interior decorators and the
 6 painters.
 7 Now, why does this matter? Well, the
 8 situations in which I suspect -- but we can't show --
 9 that the prior and the posterior are similar -- that
 10 is, that the consumer has some, you know,
 11 understanding that, say, everybody's regulated -- are
 12 actually precisely the same situations in which the
 13 consumer would care about the regulation status, which
 14 is to say regulation of painters might be dumb, and we
 15 see that the consumers don't -- you know, the
 16 consumers didn't know whether the -- it's possible the
 17 consumer didn't know whether or not the painter had a
 18 license, and the consumer doesn't care, and they're
 19 probably right not to care.
 20 But we can't take from the results that the
 21 consumer doesn't necessarily care about the
 22 electrician or the plumber, because the consumer
 23 hasn't actually possibly been updated that much about
 24 the probability that the electrician and plumber is
 25 licensed by seeing the license verified on the site,

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1 given this consumer probably thinks that anyone doing
 2 business as an electrician or plumber has occupational
 3 licensing.
 4 So I would want to just be careful about that
 5 idea, that in both of the situations I described, we
 6 could find that reviews matter much more than licenses
 7 in motivating consumers to hire, but that's not
 8 exactly the same thing as saying a consumer would
 9 willingly hire an unlicensed plumber, all right? So I
 10 think we just have to be careful about the
 11 interpretation there. And it might be that there's
 12 some things that could be done to try to look at that
 13 heterogeneity.
 14 Now, let me turn to the second result, which
 15 are the results about the stringency of licensing
 16 regimes, and here the authors find somewhat compelling
 17 evidence that more stringent licensing regimes lead to
 18 less competition and higher prices -- that should be
 19 kind of satisfying to us as economists, because we
 20 expected that to be true -- and also maybe less
 21 satisfying, no detectable effect on consumer
 22 satisfaction. So consumers are paying more in the
 23 circumstance in which they're in a location with more
 24 stringent licensing for the particular profession that
 25 they're looking at but also, you know, don't end up

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1 any happier about the job that's been done.
 2 Here I do think we have to pause a little bit
 3 to think about the difference between what we think,
 4 say, the education in the occupational license is
 5 teaching and what are the things that consumers care
 6 about or measure. I think the results here are most
 7 compelling in situations in which, you know, the kind
 8 of things that the license would measure are things
 9 that a consumer would sort of immediately be able to
 10 detect, right? Then we would in some circumstances
 11 expect to see some relationship between satisfaction
 12 and ratings.
 13 But there are two kinds of things that the
 14 licensing might be teaching, let's say the educational
 15 requirements. One might be the kind of things that
 16 are observed only down the road, right? So the
 17 plumber who comes is nice, he seems to do a good job,
 18 I give him a high rating, but does it leak later,
 19 right?
 20 And then I think another thing we should think
 21 about, which is a compelling case for regulation but,
 22 again, would get -- and would give us exactly these
 23 results, but wouldn't necessarily make us think the
 24 regulations are bad, are any situations in which the
 25 education or the regulations are on things that

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1 consumers systematically underscreen for relative to
2 social welfare.

3 So what would be some examples of that? I'm
4 pretty sure some of the training for the pest
5 companies is about safe disposal of pesticide. The
6 consumer might not care about that. It might not
7 affect consumer satisfaction, but if you think poor
8 disposal of pesticide is an externality, we want
9 higher prices, and the consumers won't be happier.
10 Similarly, occupational safety kind of stuff for a
11 roofer would be the sort of thing we might regulate,
12 it might be part of the occupational licensing, but we
13 might expect these effects.

14 Here again, I think one thing the paper could
15 do, which I think would help a lot, is just a little
16 more color on what the licenses -- you know, what does
17 the educational program look like? And maybe a little
18 more digging into the heterogeneity across the various
19 kinds of occupations. But my guess is that I believe
20 you, that there's pretty compelling results here, that
21 there's some sets of occupational licenses in these
22 building professions or home services professions that
23 probably don't create a lot of value for consumers.

24 Thanks.
25 (Applause.)

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1 MR. ROSENBAUM: All right, we have time for
2 some questions.

3 AUDIENCE MEMBER: Hi. First of all, as an
4 economist, I thank you from a very -- professional or
5 occupational licenses are pretty important, you know,
6 I don't think too many universities allow people
7 without Ph.D.s to teach. I wonder what our licenses
8 are good for, but...

9 So the one table actually that caught my
10 attention is where you ran these regressions,
11 licensing but also reputation variables, and you had
12 these very nice instruments for both price and
13 reputation. Typically what we think about in
14 reputation in online settings is, you know, the
15 reputation score is correlated with other stuff in the
16 listing, and it's, you know, maybe upward biased to,
17 you know, capturing, but when you do the IVs, those
18 coefficients jumped up by two or three orders of
19 magnitude, from very low to extremely, extremely high.

20 So do you have an explanation for why -- I know
21 this paper is very preliminary, but I've never seen
22 coefficients change that way.

23 MR. FRADKIN: Ah, I don't -- I've never
24 investigated what causes the jump in terms of
25 examining, like, the details of that, but --

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1 AUDIENCE MEMBER: It goes from one basis point
2 to, like --

3 MR. FRADKIN: My sense is that maybe as you
4 accumulate reputation, you start winning different
5 types of jobs, which -- I don't know, which -- which
6 might be harder to fulfill or something like that.
7 I -- but I -- I don't really -- I don't have a good
8 intuition for that. I'll have to think about it more.

9 MS. JIN: Yeah, I'm interested in the
10 interaction of the two results you show. If we go
11 with the consumer side result, that consumer did not
12 care so much about licensing, and if -- even if you're
13 not licensed, you can still bid and get selected by
14 consumers on this platform, which sort of is not
15 exactly consistent with the second result, that
16 licensing actually reduce competition, and if I can
17 get in the market, that sort of suggests that whatever
18 the regulator is not enforcing that licensing
19 requirement very stringently; however, somehow it
20 still have this lessened competition effect. So do
21 you have any comment on that?

22 MR. FRADKIN: Yeah. So I think for a lot of
23 these professions, there are these kind of, you know,
24 \$500 thresholds, so it's perfectly reasonable for
25 there to be both licensed and unlicensed pros to be

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1 operating and competing with each other, but the fact
2 that some of the -- in order to compete for some of
3 the jobs, you need a license, that's going to affect
4 the entire market structure. So I think that's one
5 reason that you could reconcile these results.

6 AUDIENCE MEMBER: So here in your results you
7 were showing that there is a correlation between
8 five-star ratings and licenses, but that goes away
9 when you control for reputation and other
10 characteristics. So what I'm wondering is, is it
11 common because people do not update or include their
12 licenses early enough, that -- like if I -- when I'm
13 very new to the system, maybe at that time, when I
14 have my licenses in the system, it will help me, but
15 the value of the license will go down when I have
16 built up my reputation? So if I'm there for two years
17 and I had probably license all the time, I just didn't
18 upload it on the system, it -- after two years, it
19 would not have any effect, but if I had done it right
20 away, it would have had some impact for my future?

21 MR. FRADKIN: Yeah. So we haven't done that
22 heterogeneity analysis, and we can check for that, but
23 at least when we think about how consumers react to
24 the verified licenses when they're making their hiring
25 decisions, we weren't able to find kind of very

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1 smoking gun interaction effects in the amount of
2 experience that you have and whether you got the
3 verified license or not, in terms of how consumers are
4 hiring them, the pros.

5 MR. RASMUSEN: Okay. Well, that was my
6 question, but I'll ask another one. So you did the
7 interactions and no effect came up between experience
8 and license?

9 MR. FRADKIN: I mean, it's inconsistent. It's
10 hard to -- like, depending on the specification, we'd
11 get -- we'd kind of get all sorts of weak effects.

12 MR. RASMUSEN: A lot of ways to do it, yeah.
13 Anyway, I'll suggest something more along the line of
14 Judy's, in that one good reason for licenses would be
15 so you can take them away if the person misbehaves.
16 It doesn't apply so much to painters. They might
17 burglarize your house or something, but otherwise you
18 could have a system where you pay a hundred dollars to
19 take away your license and put you on an online list,
20 and I know Indiana -- and there may be other states --
21 have online all the horrible stories of people you
22 might hire for something.

23 MR. FRADKIN: Yeah. So I've seen those lists
24 as well. We haven't thought about incorporating them
25

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1 into this analysis, but I'll think about it more,
2 yeah.

3 AUDIENCE MEMBER: So I'm thinking about this,
4 coming back to the platform outcome variable on the
5 left-hand side, and I think it might be working
6 against you on some level, because if I have a house
7 with many electrical problems, I go to the platform, I
8 find a good electrician, the next time I have an
9 electrical problem, if I'm happy, I'm not coming back;
10 I'm just calling that person, right?

11 So on some level, not coming back to the
12 platform in the same category is a good outcome, not a
13 bad outcome. So maybe there's a way of breaking apart
14 coming back to the same category versus coming back
15 for something unrelated and seeing if that helps you
16 out.

17 MR. FRADKIN: Yeah, that's a great suggestion.
18 We haven't done that yet, but that would work.

19 AUDIENCE MEMBER: This is sort of orthogonal to
20 your research question, but is there any sense in
21 which there are other effects of occupational
22 licensing that -- on the firm side? Like can firms be
23 insured if they are not licensed in certain states,
24 and if you slip and fall in somebody's house while
25 painting, like, most of the time you wouldn't if there

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1 was a five-star review, but do you know whether -- how
2 things like that work with licensing?

3 MR. FRADKIN: So my understanding is that some
4 but not all licenses require insurance. I think it
5 depends on the profession. Oftentimes, the pro will
6 signal in their profile text that they are insured,
7 but it doesn't happen, like, an overwhelming amount of
8 the time. So I -- that's -- that's something that we
9 are going to have a hard time studying in this paper,
10 but I agree that that could also be important, and
11 especially to the extent that getting insurance might
12 be more or less difficult for certain types of
13 individuals.

14 AUDIENCE MEMBER: So it's not -- okay, yeah, we
15 can talk about it.

16 MR. FRADKIN: Yes.

17 MR. ROSENBAUM: Thank you.
18 (Applause.)
19 (End of session.)
20
21
22
23
24
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1 PAPER SESSION:
2 DIAGNOSING PRICE DISPERSION

3 MR. PETEK: All right. We are ready to get
4 started again. Our last paper session of the day is
5 chaired by Ali Hortaçsu. I'm Nathan Petek. I'll be
6 introducing the speakers. The first speaker is Matt
7 Grennan, who is going to present Diagnosing Price
8 Dispersion.

9 MR. GRENAN: All right. I want to say thank
10 you to the organizers for putting on this great
11 conference and the organizers and Ali for including us
12 on the schedule today.

13 So this paper is part of an agenda that Ashley
14 Swanson -- sitting over here -- and I have on thinking
15 about the prices that hospitals pay for medical
16 technology inputs, and it turns out that if you look
17 at the exact same input at the exact same point in
18 time sold by the same vendor and then look across
19 hospitals, they will be paying quite different prices
20 for that same thing.

21 This figure right here is representing that by
22 looking at a given product, looking across hospitals
23 at a point in time, and taking the coefficient of
24 variation -- so the standard deviation over the
25 mean -- for that particular product, and then this is

173	<p>1 summarizing that over products for a bunch of 2 different product categories. So each of those dots 3 or squares or triangles you see there is the mean of 4 that measure for a product category, and then the bar 5 you see around that is the inner quartile range among 6 products in that category. 7 So the take-away from this is that there's a 8 lot of this price dispersion across hospitals or 9 across buyers for the exact same thing, no matter if 10 you're looking at some of these PPIs, or physician 11 preference items, you know, these are like the 12 high-tech medical items, you know, stents, pacemakers, 13 hip and knee implants, ranging, you know, from those 14 on to kind of more commoditized items, you know, like 15 needles, surgical gloves, and so on. 16 And these price differences are pretty 17 meaningful to a hospital's bottom line. So hospitals 18 run on pretty thin operating margins, so the average 19 AHA survey margin in 2013 was about 3 percent, and 20 these -- and the supplies that are in the database 21 that we're going to analyze today represent about 23 22 percent of hospital operating costs. So if you do the 23 back-of-the-envelope math here, you're moving one 24 standard deviation, and all of these supplies would be 25 kind of equivalent to going from the average to going</p>	175	<p>1 negotiated outcomes. 2 And then also you could think of things along 3 the lines of just contract structure, right? So are 4 there nonlinear contracts in here, some sort of 5 bundling, some sort of exclusionary behavior, and so 6 on? 7 And, finally, you know, you look at some of 8 these much more commoditized products, and you think 9 about, you know, what is potentially driving market 10 power here? And it reminds you immediately of kind of 11 the Stigler, you know, thinking about why is there 12 price dispersion among buyers for a commodity product? 13 Well, some sort of search costs, or think about here 14 much more broadly, as I'll say search costs many times 15 during this presentation, but what I really want you 16 to think of is kind of the full set of things that go 17 into forming a buyer-supplier relationship, right? 18 So think not only kind of finding a potential 19 supplier, but all the kind of due diligence and work 20 that goes into figuring out and developing a 21 contracting relationship. And, you know, along those 22 lines, you might think that these could be important 23 in this particular setting. 24 So in this paper today, we're going to try and 25 say something about all these aspects. So today the</p>
174	<p>1 to, you know, redlining it. 2 So these are pretty meaningful differences, and 3 so we want to look at what's underlying some of this 4 variation across hospitals, and then we want to look 5 across these very different product categories and see 6 the extent to which those underlying features may be 7 similar or different. 8 And so why does this kind of law of one price 9 tend to fail here? So there could be many reasons, 10 right, many of which a lot of people in the audience 11 here have studied, and, you know, one would just be 12 there is some sort of brand preferences, right? So 13 these are differentiated products, and maybe the 14 preferences over these differentiated products are 15 different among physicians or providers at different 16 hospitals, and that's some of what we're seeing here, 17 right? 18 Another would be a variety of explanations on 19 the supply side, so maybe distribution costs may vary 20 somehow, and some of that's what we're seeing; maybe, 21 you know, these are negotiated prices typically 22 between the vendors and the hospitals and, you know, 23 perhaps that bargaining parameters within that 24 negotiation are different; information folks may be 25 something that's driving differences in those</p>	176	<p>1 distribution cost one is on the agenda but kind of not 2 going to be underlying any of the things you see 3 today, so just keep that caveat in mind. 4 On the contract structure, it's not going to be 5 built into the model I'm going to show you, but we do 6 a lot of work both in this paper and in a previous 7 paper -- you can look at the 60-page appendices if you 8 want to -- to just kind of do everything we can check, 9 both in terms of, you know, qualitative efforts and 10 interviewing people and also all of the checks that we 11 could think of in the data. 12 Really, we find very little evidence of kind of 13 any underlying kind of complicated contract structure 14 or bundles underlying this. So for today we're going 15 to think of this as mostly being driven by some 16 combination of potentially demand heterogeneity or 17 brand preferences, heterogeneity in bargained 18 outcomes, and the heterogeneity in these kind of 19 search or contracting costs. 20 Now, you might ask me, you know, this log 1 21 price, everybody knows it's not supposed to be a law. 22 You just gave me a bunch of reasons why it shouldn't 23 hold, so why should I be so interested in this? Well, 24 you know, you can't get this kind of price 25 heterogeneity unless it's all driven by these kind of</p>

177	<p>1 differences in distribution costs, for example, 2 without having pretty large markups, right? And so 3 when we talk about what's underlying price 4 heterogeneity, we're really in part talking about 5 what's underlying what are potentially some relatively 6 large markups in this industry, right? 7 And, you know, related to that, you know, 8 knowing the sources of these markups is going to be 9 important as we think about, you know, what might be 10 the potential remedies or what we might expect to come 11 of various policies or kind of things that are 12 happening out there in the economy, right? So one of 13 the things that, you know, we all worry about or 14 people think about in every industry is when is Amazon 15 coming? 16 So there's been a lot of talk in the medical 17 supply industry. Amazon hired the COO of Cardinal 18 Health about a year ago and has been looking into this 19 area. So you can imagine, you know, what would that 20 kind of information or that kind of intermediary do in 21 a world like this? 22 You know, another thing, you know, these 23 bundled payments and moves towards physicians maybe 24 internalizing more of the costs of the decisions they 25 make, you might think is something that would affect,</p>	179	<p>1 vendors, and that's typically the job of an 2 administrator at a hospital, so they are the one who's 3 in charge of negotiating these contracts, making sure 4 that there is something on the shelf when a provider 5 goes there and needs to get something done. 6 Now, we drew the box there around the providers 7 as well because, you know, perhaps there's input from 8 providers in this, right? So, in particular, with 9 some of these things, like physician preference items, 10 like a coronary stent, a surgeon is going to be pretty 11 upset if he goes and he likes to use the Medtronic 12 stent and it's not on the shelf when he goes to use 13 it, and the administrator is likely to hear about 14 that. So an important part of what we're going to do 15 today is going to have to be thinking about the 16 formation of these buyer-supplier, you know, choice 17 sets, potentially with input from the people who are 18 actually using them, the physicians. And then, 19 finally, once things are on the shelf and there to be 20 used, providers are going to make decisions as 21 patients come in in order to do their best to treat 22 those patients. 23 And then another important feature of what 24 we're going to do today is that this sort of activity 25 is going to happen across lots of different product</p>
178	<p>1 for example, brand preferences and so on. 2 And then, finally, you know, we are going to be 3 looking across quite a -- you know, these are all 4 medical supplies, but it's quite a heterogenous and 5 large group of different categories here, so you'll 6 recognize the approach that we take as being a very 7 traditional IO approach, but we are taking it across, 8 you know, a pretty large number of product markets, 9 and so, you know, hopefully building towards this idea 10 of, you know, we want more evidence in more areas 11 along the -- you know, the -- building towards what 12 the macroeconomists want from the IO world. 13 Okay. So I'll talk a little bit more about 14 this institutional context, give you an idea for what 15 we're working with here, the data set that underlies 16 this entire endeavor, and then how we try and break 17 down these pieces of the price dispersion. 18 Okay. So we're thinking about hospitals 19 contracting with suppliers in, say, a given product 20 market. So here I've just shown you the kind of set 21 for coronary stents, because it's very simple. There 22 are three vendors. It's probably the most 23 concentrated, I think, of any of the markets that we 24 look at here. And, you know, a hospital is going to 25 be thinking about potentially contracting with its</p>	180	<p>1 categories within the hospital, some of them being 2 relatively far away from one another. So what do I 3 mean by far away? I mean something like, you know, 4 coronary stents, they are used in interventional 5 cardiology in the catheter lab, versus, say, neurology 6 devices, which may be sold by the same vendor but sold 7 by an entirely different sales force to an entirely 8 different set of physicians and surgeons. And we are 9 going to try and leverage the fact that there may be 10 some linkages between these, you know, not on the 11 demand side, but on the kind of cost side, on the 12 administrator front, in order to get some mileage in 13 solving some of the challenges of identification in 14 this setting. 15 Okay. So a key that makes this whole endeavor 16 possible is there's a really cool data set on 17 basically everything these hospitals purchase, so it's 18 about 20 percent of U.S. hospitals over the course of 19 six years. We see all the purchase orders they issue, 20 so prices and quantity, at the -- kind of the -- you 21 should think of it as, like, the stockkeeping unit 22 level, so not only just the product that you know the 23 manufacturer and the vendor of that, but also, like, 24 the size of that product, and it's for lots and lots 25 of different SKUs across lots and lots of different</p>

181	<p>1 product categories on a monthly basis.</p> <p>2 And, you know, there are many challenges in</p> <p>3 dealing with this data and kind of working it into a</p> <p>4 format that we would do traditional supply and demand</p> <p>5 analysis with, and for today's short presentation, I</p> <p>6 will refer you to the many, many appendices,</p> <p>7 especially in the previous paper but some in this</p> <p>8 paper, about those. I guess right now I just want to</p> <p>9 make the -- start to point out, the way I'll try to</p> <p>10 summarize this is -- so in the paper, the current</p> <p>11 version, we have 24 different kind of non-PPI</p> <p>12 categories and six different physician preference item</p> <p>13 or PPI categories. So as I said before, these</p> <p>14 preference items are going to be things like</p> <p>15 pacemakers, drug-eluting stents, hip and knee</p> <p>16 prostheses.</p> <p>17 The non-PIPs are going to be a little bit more</p> <p>18 heterogenous. So in there you'll see things that</p> <p>19 sound pretty commoditized, like surgical gloves, like</p> <p>20 sutures, and, you know, trocars are something that's</p> <p>21 used in laparoscopy procedures, a fairly common item,</p> <p>22 to things that are starting to get maybe more closer</p> <p>23 to PPIs, like a bone nail, right, but something that</p> <p>24 you maybe think is -- you know, a bone nail would</p> <p>25 typically be used, for example, in a prosthetic</p>	183	<p>1 of a price within that category, and that coefficient</p> <p>2 of variation is going to be similar to one I described</p> <p>3 to you before. So take a given product at a given</p> <p>4 point in time, look across hospitals, calculate the</p> <p>5 coefficient of variation, and then to give you just</p> <p>6 one number here for a category, we are just going to</p> <p>7 quantity-weight that number across all the different</p> <p>8 products in that category, okay? But, again, as you</p> <p>9 can see here, the quantity weighting kind of lowers us</p> <p>10 a little bit, so some of those huge coefficients of</p> <p>11 variation were coming from less used products but</p> <p>12 still quite large, on average 13 percent.</p> <p>13 The other thing that you'll see varies here is</p> <p>14 the kind of size of the potential choice set, so</p> <p>15 there's the script J here, right? So this is the set</p> <p>16 of products used across all hospitals at a given point</p> <p>17 in time in the data, on average, and then that --</p> <p>18 comparing that to the script J with the h subscript,</p> <p>19 which would be the size of the choice set we observe</p> <p>20 for a given hospital on average in the data.</p> <p>21 So you can see, you know, we're looking at</p> <p>22 something like 10 percent or less of all the products</p> <p>23 that all hospitals are using will be used on average</p> <p>24 by a given hospital, and there's a lot of variation in</p> <p>25 that measure as well across hospitals, even more than</p>
182	<p>1 procedure, but it's not kind of, like, the core item</p> <p>2 that's being put in typically in said procedure,</p> <p>3 right?</p> <p>4 And so today mostly I'll just refer you to</p> <p>5 these rows that say "average," which is like the</p> <p>6 average of all these results across those two</p> <p>7 different big categories, but I threw in six of the</p> <p>8 line items just to give you a sense here, and the</p> <p>9 paper has all -- has the results for every single</p> <p>10 category.</p> <p>11 So what you see immediately is these non-PPIs</p> <p>12 are used more often, right, so these tend to be kind</p> <p>13 of more ubiquitously used items both in terms of the</p> <p>14 numbers of hospitals that use them and the frequency</p> <p>15 with which they are used, but they are lower priced</p> <p>16 items typically, right? So actually once you kind of</p> <p>17 multiply P times Q, the actual spend on these PPIs</p> <p>18 tends to be about double of that of the non-PPIs.</p> <p>19 And you'll also see, you know, as we documented</p> <p>20 in that first figure I showed you, that the prices are</p> <p>21 quite different across hospitals for all of these</p> <p>22 different categories. So whenever I show you a</p> <p>23 summary statistic in this case -- so, for example, the</p> <p>24 price is there -- that's going to be the</p> <p>25 quantity-weighted mean across all of our observations</p>	184	<p>1 there is in the prices, right? So you have some</p> <p>2 hospitals that source quite a few different things</p> <p>3 from different vendors, some hospitals who source only</p> <p>4 a few.</p> <p>5 And then, you know, there are some other hints</p> <p>6 in there -- in here that there may be some combination</p> <p>7 of either contracting frictions or heterogeneity in</p> <p>8 preferences. So just a few kind of, you know, simple</p> <p>9 statistics that start to get at this is if you take J</p> <p>10 star here to be, say, the most commonly used product</p> <p>11 in a given category, how frequently is that most</p> <p>12 commonly used product in the choice set of a given</p> <p>13 hospital, all right? So about 34 percent of the time</p> <p>14 for the non-PPIs versus 60 percent of the time for the</p> <p>15 PPIs. And similarly, you know, how often is that</p> <p>16 actually also the most used product within a given</p> <p>17 hospital, right? So how it kind of correlated our</p> <p>18 purchasing patterns across hospitals, and only 16 and</p> <p>19 25 percent of the time.</p> <p>20 So, you know, it's -- we find it at least</p> <p>21 pretty striking that you kind of see all these hints</p> <p>22 of lots of heterogeneity in purchasing decisions, and,</p> <p>23 in particular, in some of these non-PPIs, where you</p> <p>24 might think, ex ante, at least, it's kind of our prior</p> <p>25 that there's kind of maybe less inherent</p>

185	<p>1 differentiation among some of these products, right?</p> <p>2 Okay. So just a few kind of things to talk</p> <p>3 about, kind of what may and may not be underlying some</p> <p>4 of this variation we see across hospitals. So it</p> <p>5 turns out, looking at prices, there aren't too many</p> <p>6 observables you can throw at it that explain too much</p> <p>7 of the meaningful price variation, so -- you know, in</p> <p>8 terms of -- observables in terms of hospital</p> <p>9 characteristics, so this is looking at -- just for</p> <p>10 stents, looking across bed size bins of hospitals and</p> <p>11 box plots for each bed size bin. As you can see, kind</p> <p>12 of no real discernible pattern in terms of bigger or</p> <p>13 smaller hospitals getting better deals.</p> <p>14 It's the same if you look at stents for other</p> <p>15 hospital characteristics, like is it a teaching</p> <p>16 hospital or not? Is it a public or private hospital?</p> <p>17 And, you know, if you look at the relationship between</p> <p>18 price and bed size across all these different product</p> <p>19 categories, for some there will be a -- you know, a</p> <p>20 negative relationship, for some a positive</p> <p>21 relationship, but invariably, it's a pretty small</p> <p>22 relationship. So it's never explaining a lot of the</p> <p>23 variation that we're seeing in prices.</p> <p>24 Similarly, these choice sets, you know, getting</p> <p>25 back to, you know, the institutional setting that we</p>	187	<p>1 people who have larger or smaller choice sets that</p> <p>2 they're sourcing from, you know, how does that relate</p> <p>3 to the prices that they're paying?</p> <p>4 And, you know, in particular we think of it as</p> <p>5 interesting in thinking, you know, back to these</p> <p>6 issues of, you know, one reason you might have a small</p> <p>7 set of suppliers would be, you know, you have these</p> <p>8 contracting frictions that keeps your set of suppliers</p> <p>9 smaller than they might otherwise be. Another reason</p> <p>10 would be you're doing this strategically. You're</p> <p>11 excluding some suppliers so that you can leverage</p> <p>12 better prices from the suppliers that you, in fact, do</p> <p>13 buy from, right?</p> <p>14 And, you know, the prior would have this very</p> <p>15 strong, if this were like a well identified kind of</p> <p>16 causal regression, a very strong prediction of a</p> <p>17 negative relationship between the size of the number</p> <p>18 of people you buy from and the price, whereas, you</p> <p>19 know, that prediction would be a little bit more</p> <p>20 complicated in the second.</p> <p>21 And so, you know, we do find it at least</p> <p>22 suggestive, the evidence from this, that the</p> <p>23 relationship tends to be -- tends to be negative</p> <p>24 between these two things, and we do, you know, a</p> <p>25 little bit more work on this both in kind of this more</p>
186	<p>1 were talking about before, one of the things that is</p> <p>2 quite predictive, actually, of whether or not a</p> <p>3 product is in your choice set in a given category, in</p> <p>4 a given hospital, is the spend of that hospital with</p> <p>5 that same vendor in other hospital categories, and you</p> <p>6 can do this by other hospital categories that are near</p> <p>7 and far here. I'm just showing for far, because those</p> <p>8 are going to be the ones we are going to be interested</p> <p>9 in as kind of giving us some leverage here for</p> <p>10 identification, but, you know, if -- in some of these</p> <p>11 product categories -- so this is plotting coefficients</p> <p>12 across categories here in a regression on, you know,</p> <p>13 product time dummy variables, vendor HRR -- hospital</p> <p>14 referral region -- dummy variables, hospital fixed</p> <p>15 effects, and looking at, you know, what's the</p> <p>16 difference between someone who's above the median or</p> <p>17 below the median in terms of spend on these far away</p> <p>18 categories. You know, for some product categories,</p> <p>19 it's quite dramatic, being above the median, you know,</p> <p>20 like double your propensity to be in a given hospital.</p> <p>21 And then, finally, how do these two things</p> <p>22 correlate, right? This is obviously a quite</p> <p>23 speculative regression that doesn't have, you know, a</p> <p>24 lot of causality behind it, but nevertheless, I think,</p> <p>25 you know, interesting to think about, you know, for</p>	188	<p>1 reduced-form analysis and then in some ex post</p> <p>2 analyses after we get our demand estimates that I</p> <p>3 won't have time to go into today, but our take-away</p> <p>4 from the entire endeavor, that at least in these</p> <p>5 product categories, it seems that the story is not</p> <p>6 really one of exclusion being a strongly suggested</p> <p>7 thing that's going on in this data set.</p> <p>8 Okay. So how are we going to, in fact,</p> <p>9 disentangle these features, right? So we kind of have</p> <p>10 these three items that I told you about, all</p> <p>11 interrelated with one another potentially, and we're</p> <p>12 going to have to think about how we disentangle them.</p> <p>13 And so, you know, what we're going to do is</p> <p>14 think about, you know, a model where, you know, a</p> <p>15 hospital has some ex ante beliefs over the qualities</p> <p>16 of some products, so maybe some product time quality,</p> <p>17 some, you know, vendor HRR quality on average, my</p> <p>18 hospital kind of needs, you know, preferences on</p> <p>19 average, with some unknown components, at least</p> <p>20 unobserved to the econometrician, these XCs, right,</p> <p>21 and kind of the twist on what we're used to seeing</p> <p>22 here is going to be that we're going to have these XCs</p> <p>23 that are unobserved to us, but one of these, the XCO</p> <p>24 is potentially observed to the hospital before they go</p> <p>25 out and contract with a vendor. So this is what I was</p>

189	<p>1 talking about before with this idea that, you know, 2 maybe physicians are influencing administrators and 3 making these sourcing decisions, and that might be 4 moving things in a way that's difficult for us to see 5 as a researcher. 6 You're also going to have some known idea over 7 what marginal cost would be, some bargaining weights 8 that, again, you'll kind of have a sense of, on 9 average, what happens with a given provider, on 10 average what happens with my hospital, but some 11 realization of the joint bargaining split that is kind 12 of yet to be discovered until I actually do my due 13 diligence and kind of pay these costs to go and think 14 about actually contracting with these vendors. 15 And then, you know, finally, these choice sets, 16 so these script Js are going to be determined. You 17 will learn these unobserved portions, and contract 18 prices will be set. Those will be set for some period 19 of time, and physicians will treat patients as they 20 come in, and quantities will be realized. So the two 21 challenges in this setting is -- one is kind of the 22 traditional one that we're used to, is price may be 23 some function of things we don't observe in the demand 24 system, and then this kind of -- this different 25 feature where your actual choice set might be a</p>	191	<p>1 actually provides information to hospitals on what 2 other hospitals are paying for prices or paying for 3 different items, and in that paper we found that it 4 seemed to be highly suggestive of an asymmetric 5 information story, where when you found out that you 6 were really in the far tail of prices for things that 7 you were purchasing a lot of, your prices tended to go 8 down subsequent to getting this benchmarking 9 information, and we are going to use that here as an 10 instrument that's shifting around price exogenously in 11 order to help us get some identification on the price 12 coefficient. 13 And so we're going to have a -- you know, a 14 demand and supply system here that's going to be kind 15 of a simple nested logit with a nest on the outside 16 good, hospital fixed effects, product time fixed 17 effects, you know, the selection correction, kind of 18 your standard Heckman type thing with the demand 19 instruments that I just mentioned, kind of standard 20 Nash-in-Nash bargaining problem on the pricing side, 21 where, you know, a bunch of those parameters are going 22 to come from the demand side. We're going to 23 parameterize marginal cost in bargaining, you know, 24 embedding that sort of "do you have access to 25 information or not" inside the bargaining</p>
190	<p>1 function of your preferences if physicians are 2 influencing the choice set. 3 Okay, and so our approach for the latter is 4 going to be to look for items that are pushing around 5 search costs and, therefore, pushing around the choice 6 set. And our approach is going to be very similar to, 7 you know, the traditional selection correction that we 8 all learn kind of in the labor context, and, you know, 9 in this case, you know, the preferences of hospitals 10 might be -- who actually buy a given product might be 11 higher than the average hospital out there, and we are 12 going to use a control function approach where what we 13 are going to do is estimate what's the expected value 14 of this unobservable for a hospital that actually 15 contracts for this given product, and it's going to be 16 based on kind of a reduced-form version of what you 17 might think of as a search model that's going to 18 include these far away spend variables as the excluded 19 instruments that are uncorrelated with demand but only 20 correlated with search costs in the choice set. 21 Okay. Then we're also going to have to tackle 22 our more standard price endogeneity problem, and there 23 we're going to leverage the previous paper that we 24 wrote with this data set. So the reason this data 25 exists, it's a hospital benchmarking platform that</p>	192	<p>1 parameterization, and jointly estimate the whole thing 2 via GMM. 3 All right. And so this would usually be the 4 part where I would tell you about how we go about 5 estimating search costs, but since I'm already 6 actually out of time apparently, it's a good thing 7 that I'm skipping ahead and going to summarize that 8 for you briefly. So what comes out of the demand and 9 bargaining estimates, the thing that was probably most 10 surprising to us was this extreme price insensitivity 11 across kind of all these product categories, right? 12 So PPIs are much less price-sensitive than 13 non-PPIs, but all of these categories, you just don't 14 see much price sensitivity in demand, and so that's a 15 big thing that's underlying these kind of markups that 16 we're seeing in this market. So the markups on 17 average are, like, 20 to 80 percent, and so actually 18 it turns out that the fact that prices are negotiated, 19 that hospitals have some monopsony power is really a 20 key element that's keeping prices down actually 21 relative to what they otherwise would be in this 22 market. 23 So just two exercises to wrap up that we looked 24 at to try and disentangle more what's going on in this 25 market, so what's the role of these search frictions.</p>

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1 The first we look at, you know, in this -- you can
2 imagine if you're familiar with these various search
3 models, what we're talking about here is a relatively
4 complex problem, right? You're sort of searching for
5 a set of suppliers who you're going to kind of
6 continually purchase from, so basically a portfolio
7 that you're searching over. There's lots of
8 heterogeneity in the demand and pricing specifications
9 that I showed you, and so this is going to be a very
10 complex search problem with large potential state
11 spaces.

12 So the approach we are going to use to try and
13 actually estimate these search frictions is going to
14 be using moment inequalities, you know, based on some
15 necessary conditions for products being in the choice
16 set, and I think the slightly -- you know, the slight
17 innovation or twist we have on some of the other
18 papers that have been out there in this space is we've
19 come up with these kind of loose conditions that we
20 argue are consistent potentially with many different
21 models of search or choice set formation.

22 Those costs end up being about on the order of
23 10 percent of price, so, you know, meaningful when we
24 think about what markups are out there, but not huge
25 compared to, say, like the price insensitivity.

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1 Then finally what we do is a decomposition
2 exercise where we, one, shut down bargaining
3 variation, see what kind of variation we see across
4 hospitals in that case, recompute equilibria, and so
5 on. Two, shut down demand estimation, see what kind
6 of variation we see across hospitals in that world.
7 And then maybe more interestingly just do a very
8 extreme counterfactual where what if everyone -- there
9 were no search frictions? Everyone had access to the
10 entire choice set that's available out there, what
11 would we see?

12 And what we find actually is that the prices
13 would go down a little bit, but not a ton, right? So
14 on the order of something like 5 percent price
15 reductions you're seeing here, and what you're
16 seeing -- you know, much bigger effects that would
17 come from that is potential, you know, consumer
18 surplus gains through the additional variety and
19 access to quality, right?

20 I don't want to hang my hat on that totally,
21 because those who have worked with these models know
22 there's a lot of extra logit errors being thrown in
23 there, in that consumer surplus analysis, but I think
24 the take-away is here is that the price implications
25 of contracting frictions don't seem to be huge here.

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1 You know, the big story is this lack of price
2 sensitivity in this market that generates a lot of
3 market power, this bargaining by hospitals that holds
4 that market power down, but there's a lot of
5 heterogeneity in these bargaining parameters that
6 we're estimating here that's leading to the price
7 dispersion that we see.

8 So we still have plenty of work to do on this
9 paper, and I'm way over time, so I will stop and
10 listen to your comments on that. Thank you very much.

11 (Applause.)

12 MR. PETEK: So Tobias Salz will discuss Matt
13 and Ashley's paper.

14 MR. SALZ: So, yeah, let me already start by
15 saying or thanking the organizers and Ali for allowing
16 me to discuss this paper. This is something that I'm
17 personally very interested in, and it was a lot of fun
18 to think about it, and I really like this idea of this
19 decomposition. So if you work on search models, you
20 are oftentimes asked, well, is this not just some sort
21 of bargaining friction instead? And I would not
22 disagree with that. So I think this is a super
23 valuable exercise and -- yeah, so I'll jump into the
24 details here.

25 Let me spend one slide actually on motivating

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1 this question. So the -- this literature, I mean,
2 very broadly -- and I may be oversimplifying at this
3 point -- asked, what is reflected in a price? And
4 this started with the observation that we see a lot of
5 price dispersion in markets where we shouldn't expect
6 it; namely, for example, retail financial products
7 where we can arguably very well control for all the
8 quality attributes that buyers should care about. And
9 the explanation is that there's some sort of friction
10 that prevents buyers from picking the optimal -- the
11 optimal product for them.

12 And recently, there's also a literature that
13 argues that we see a lack of state contingent pricing,
14 so sort of the opposite of this, right, that -- in
15 particular, within retail chains across locations,
16 there seems to be less catering to local demands than
17 we would expect. And one explanation that's been
18 brought forward here is that this might be due to some
19 sort of managerial fixed cost that prevents firms from
20 charging the optimal price.

21 And so, arguably, in this paper, both of these
22 explanations are relevant. So this is a
23 business-to-business market where suppliers might, due
24 to some frictions, not set the optimal prices that
25 shows up here in the bargaining, in the relative

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1 bargaining parameters, and on the demand side, there
2 is a friction that prevents from finding what the
3 optimal set of products would be. And what makes life
4 even harder here is that on top of these two
5 explanations, there might also be, of course,
6 preference heterogeneity and cost heterogeneity.

7 Now, as Matt has pointed out and as you are
8 probably well aware, you know, what -- the true
9 underlying reason for price heterogeneities in this
10 market will, of course, very much determine how we
11 want to think about policy. So if it's true that this
12 is due to search frictions or some sort of
13 informational frictions, then what has recently become
14 popular in healthcare markets to provide information
15 about prices might be very valuable. If instead this
16 is due to preferences, then, of course, that would be
17 a different story. If you think about mergers, then
18 heterogeneity and bargaining ability are, of course,
19 important to understand, okay? So I think, again,
20 this is a -- it's a very valuable exercise.

21 It's also something that is actually -- it
22 takes about two minutes to find a lot of corroborating
23 evidence online from the view of practitioners. So
24 this is something that's very much in the minds of
25 practitioners, so this is -- these are two quotes from

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1 a website that's called Healthcare Finance, where they
2 basically describe that it's very important who the
3 person is that you pick for these negotiations and
4 that different hospitals have different ability to
5 solve this problem, and it's informationally a very
6 daunting task to, you know, keep track of all the
7 prices, all the vendors, and the various ways in which
8 you could purchase these things, okay? So there's
9 definitely a lot of supporting evidence for what the
10 authors have in mind here.

11 Okay, before I jump into specific comments on
12 the model, let me quickly recap -- and I'm actually
13 happy that I'm recapping, because I think Matt did not
14 get a chance to go over the search cost estimation, so
15 I'll hopefully cover this.

16 So this is a model where hospitals have
17 preferences over items that they want to source, and
18 then at some -- in some costly process, they can add
19 those items to their consideration set. And then
20 there is Nash-in-Nash bargaining, so this is a
21 standard Nash-in-Nash bargaining framework, but within
22 the set of items that have been added to this
23 consideration set, okay?

24 And so this is basically the sequence of
25 events, and now the estimation goes in reverse order

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1 of how these events occur, so they estimate jointly a
2 demand and bargaining model, where they keep track of
3 selection into this consideration set by using this
4 control function approach, and then in the last step
5 they get at these search cost parameters, and the idea
6 here is that they resolve this bargaining game to get
7 a new set of prices from which they compute the added
8 inclusive value of adding a specific item to your
9 consideration set, okay?

10 And then they basically, from those added
11 inclusive values, get conservative bounds on the
12 search costs. So you get a conservative upper bound
13 by saying that a product that we see in your
14 consideration set must have been added at some point,
15 and the most conservative bound is by adding it to the
16 empty set, right? That's when it's providing the
17 highest value.

18 And conversely, a product that is not in your
19 consideration set would provide the lowest -- so a
20 conservative lower bound -- the lowest value if you
21 add it to the entire set of products that's available.
22 That's when it provides the smallest marginal value,
23 okay? So that's how they, in a parsimonious way,
24 without having to take a stance on how the exact
25 search cost model looks like get these bounds.

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1 Now, what you see, though, is that all of this
2 depends very heavily on getting right the
3 consideration set, right? And so that's unfortunately
4 not something that's directly observed here, and I
5 think the authors made a very sensible assumption in
6 saying that this is the set of products that have --
7 you've seen purchased in the past, right, so that's
8 natural in that it leverages the panel structure that
9 the authors have access to, but -- because it plays
10 such a crucial role in the identification of the
11 bargaining parameters, but also on these bounds, I
12 want to push a little bit here.

13 So one simple thing one could do is to simply
14 make a -- instead a rolling window assumption and
15 look -- you know, sort of varying the length of this
16 window and see how robust the results are to different
17 assumptions here. But pushing this a little bit
18 further, what could also be exploited is the fact that
19 consideration sets lead to specific asymmetric
20 substitution patterns. So we all know that, you know,
21 we get other ways of -- we get asymmetric substitution
22 patterns in other ways in demand models, but
23 consideration sets say that there are asymmetric
24 substitution patterns along the boundary of the
25 consideration set, right?

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<p>1 And so I'm wondering whether the authors can 2 use this insight, which has recently been formalized 3 in Abaluck and Adams, and I'm sure there are other 4 papers that I'm not aware of, and so my guess is that 5 their approach is a bit restrictive for this market 6 with business-to-business and contract-specific 7 prices, but one thing that they maybe could do is to 8 take their definition of this consideration set and 9 see whether something that according to this 10 instrument that they use for the control function 11 approach gets randomly placed in the consideration 12 set, has other substitution patterns than something 13 that's outside of the consideration set.</p> <p>14 Now, the problem with this is that this is not 15 a posted price market, right? So you cannot just look 16 at price variation and sort of see how it -- how 17 substitution patterns adjust, because every business 18 has a specific price that depends on the relative 19 bargaining parameters and other attributes. So my 20 suggestion here would be to maybe use this 21 benchmarking database and treat it as a posted price, 22 okay, and see whether, with that, you get -- you can 23 test for these asymmetric substitution patterns that 24 you would expect to see if you get this consideration 25 set right, and maybe you can also test what the most</p>	<p>1 make one more comment on something that I find 2 personally very interesting. Actually, I learned 3 about this when I was visiting here at the FTC a while 4 ago, and Matt can take this comment with free disposal 5 because it's really speculative, but what's 6 interesting about these markets is that we have these 7 group purchasing organizations here, which essentially 8 every hospital is participating, so more than 95 9 percent of hospitals are part of these GPOs, more than 10 80 percent of all purchases are conducted through a 11 GPO, and what they essentially do is they -- I mean, 12 supposedly, you know, strengthening the bargaining 13 power of hospitals, and also provide information about 14 sets of products that are out there.</p> <p>15 It would be interesting whether this can be, at 16 least in a reduced-form way, be picked up by these 17 bargaining estimates. I know it might be hard to get 18 data on this, so that's why this is quite speculative, 19 but, you know, these are sort of a fascinating entity 20 that would provide some separate variation in 21 information and bargaining strength, separate from 22 preferences. So I think this might be quite 23 interesting to study.</p> <p>24 With this, I want to wrap up and say I think 25 this is a really interesting and insightful paper.</p>
202	204
<p>1 likely consideration set would be. And I think that 2 that would sort of go a long way.</p> <p>3 My other comment is that at the end, the 4 outcome of the paper is a decomposition exercise into 5 preferences, relative bargaining strength, and search 6 costs, and something that I'm wondering here is to 7 what extent this might be driven by a very specific 8 parameterization of these three different channels, 9 right? So if we are looking at this -- we have, for 10 example, this information variable in relative 11 bargaining strength but not in search cost, and we 12 have vendor fixed effects in the preferences but not 13 in the relative bargaining strength.</p> <p>14 So what I would like to know here is either, a 15 priori, you know, do we have strong reason to expect 16 that, you know, we have to put these objects there and 17 not somewhere else, or, you know, do we want to be 18 sort of completely agnostic and put all these things 19 into all these three different types of channels, at 20 which point, of course, you would pretty heavily rely 21 on function or form assumptions, but, you know, sort 22 of if you really want to get this decomposition right, 23 I think you need some justification for, you know, why 24 these things show up at these specific places.</p> <p>25 So I'm almost running out of time. Let me just</p>	<p>1 I've been frequently asked about this, you know, 2 decomposition to search and bargaining costs. I think 3 this will be very valuable to the profession, and I 4 think this is also something that brings together two 5 different literatures, so the search cost literature 6 has formerly been a bit separated from these vertical 7 models, and so I think in that regard it's also a very 8 nice paper.</p> <p>9 That's all I have to say. 10 (Applause.)</p> <p>11 MR. PETEK: So we have about five minutes for 12 questions.</p> <p>13 MS. JIN: It's a very interesting and 14 sophisticated paper. I'm wondering, to the extent 15 that both hospitals and suppliers are sort of 16 long-term players, they know they're going to engage 17 with each other for a long time, so to what extent do 18 you see dynamic concern show up in the data?</p> <p>19 MR. GRENNAN: Yeah, I think dynamics are a 20 great -- like an interesting point here. It's 21 something that we've incorporated a little bit by kind 22 of just putting lags, like who were you with last 23 time, and it's something that's kind of on our radar 24 screen. Basically, the kind of two main things that 25 we're still -- three main things, I guess, we're still</p>

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1 trying to wrap our heads around how to do in a way
 2 that's tractable is kind of these dynamic issues, the
 3 fact that you have vendors selling many things both
 4 within a category and across categories, and this
 5 issue of kind of potential costs or returns to scale
 6 and distribution costs. So agreed, and we're in the
 7 market for very tractable solutions to these things.
 8 MR. BRUESTLE: Hi. Steven Bruestle, Federal
 9 Maritime Commission.
 10 If a hospital is buying a lot from the same
 11 vendor, could we possibly be seeing evidence of
 12 bundling, maybe I'll give you a cut on this product in
 13 exchange for you paying a little more on that product?
 14 MR. GRENNAN: Yeah, absolutely. So this is --
 15 our prior going into this project is that we were
 16 going to be doing a lot more on trying to, you know,
 17 figure out how to extract information on kind of
 18 unobserved bundling and contract features that we
 19 weren't seeing but that were probably there. We were
 20 kind of surprised that in the first paper, when we
 21 went to go do a lot of qualitative work in just
 22 talking to people, how infrequently they seemed to
 23 talk about these things being an issue, and then once
 24 we actually went to the data and kind of the set of
 25 tests that we've thrown at it in terms of correlations

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1 between prices that you might expect to be part of a
 2 bundle, for example, or correlations in changes in
 3 prices or the comovement of prices, we're just not
 4 seeing much there.
 5 MR. BRUESTLE: Okay, great. Thank you.
 6 MR. BESANKO: So I wanted to build on the last
 7 comment that Tobias made about the bargaining weights.
 8 I thought that was actually something -- that was
 9 something that really caught my eye. As I recall, you
 10 said the bargaining -- the estimates of the bargaining
 11 weights for the vendors are somewhere between 1
 12 percent and 42 percent.
 13 MR. GRENNAN: Yeah.
 14 MR. BESANKO: So there's a lot of bargaining
 15 power by the hospitals. Do you know anything about --
 16 you know, are they larger hospitals? Are they
 17 hospitals -- are they hospitals -- or are these
 18 categories where there's a lot of bargaining weight
 19 from the hospital more commodified, more vendors? I
 20 mean, what can you tell us about the circumstances
 21 under which those bargaining weights differ?
 22 MR. GRENNAN: Yeah, thank you for reminding me,
 23 because I left out the other thing that's on the
 24 agenda that perhaps our RA is sitting in Philly
 25 running today, is actually bargaining weights on

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1 stuff. So this having hospital stuff to run it on is
 2 a relatively new thing that we have been able to do in
 3 a de-identified sort of way and something that we're
 4 very curious about.
 5 I would say anecdotally, just in our
 6 conversations with people, like, there didn't seem to
 7 be a lot of correlations based on what we would have
 8 thought, ex ante, in talking to hospital purchasing
 9 professionals, where people who seem to be good at
 10 this were going to be, right? Like, it seems to be
 11 very person-specific, organization-specific, probably
 12 variables that we're probably not going to be
 13 capturing in, like, things in the AHA or that we're
 14 seeing here.
 15 MR. RASMUSEN: If I could follow up, this is
 16 making me think of the Piketty Saez paper on CEO pay
 17 and market capitalization, because you're saying that
 18 getting a good purchasing guy is really important. If
 19 we could look at their salaries, for example, we'd
 20 expect those to be higher in the bigger hospitals, but
 21 maybe some smaller hospital thinks it's getting a real
 22 whiz at bargaining.
 23 MR. GRENNAN: I mean, that would be
 24 interesting. Like, we constantly, in having these
 25 conversations, you know, do you get paid when you get

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1 a better -- you know, when you're getting better
 2 deals, you know, there does not seem to be any
 3 formalized structure for this. It seems -- despite
 4 the great quotes that Tobias threw up there, this does
 5 not seem to be a super-mature market, as far as we can
 6 tell, in terms of, like, hospital purchasing
 7 expertise.
 8 That doesn't mean that in some places it's not
 9 a big deal, but I just think it's something that
 10 there's a lot of money being left on the table through
 11 some combination of these, like, managerial fixed
 12 costs and incentive issues and professionalization of
 13 an industry and some interaction between those.
 14 MR. RASMUSEN: Actually, you wouldn't want to
 15 use a high-powered scheme, because if you have a guy
 16 this tricky and good, he could really scam you if you
 17 gave him a percentage of amount saved or something,
 18 but it would show up in flat salary, I think.
 19 MR. GRENNAN: We should look. No, I mean, to
 20 the extent that we can --
 21 MR. RASMUSEN: Maybe we could get top five
 22 salaries.
 23 MR. GRENNAN: -- get anything that proxies for
 24 that, we should try and think about that. Absolutely.
 25 All right. Thank you very much.

209	<p>1 (Applause.) 2 (End of session.) 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25</p>	211	<p>1 retirees voluntarily decide to annuitize. Moreover, 2 when you calculate the annuity prices at which they're 3 annuitizing, they seem rather good. The markup over 4 the actuarially fair annuity is quite low. So the 5 broad, overarching question that we're trying to 6 answer today is what lessons can we learn about this 7 well functioning market that we can then apply 8 throughout the rest of the world? 9 So how are we going to do this? We are going 10 to build and estimate a really flexible, I think, 11 structural model of demand for retirement assets. Our 12 goal is going to be to recover the distribution of the 13 underlying primitives that govern annuitization and 14 welfare in this setting. 15 With those distributions, we are going to do 16 two things. The first thing we're going to do is 17 we're going to change the rules of the system to make 18 the rules of the system in Chile look more like the 19 United States. We are going to evaluate what happens 20 to the annuity demand function and to the average cost 21 curve and, ultimately, to the annuity market 22 equilibrium when you move the rules of Chile to the 23 rules of the United States. 24 As a preview, I'm going to show you that with 25 Chilean preferences and Chilean rules, you get an</p>
210	<p>1 PAPER SESSION: 2 COMPETITION, ASYMMETRIC INFORMATION AND THE ANNUITY PUZZLE: 3 EVIDENCE FROM A GOVERNMENT-RUN EXCHANGE IN CHILE 4 MR. PETEK: All right. Our next speaker is 5 Gaston Illanes, who's going to present Competition, 6 Asymmetric Information, and the Annuity Puzzle: 7 Evidence From a Government-Run Exchange in Chile. 8 MR. ILLANES: So, hi, everyone. Thanks a lot 9 for having me. I'm very excited to be here. This is 10 joint work with Manisha Padi, who is at the University 11 of Chicago Law School. 12 So there's a vast literature in public finance 13 documenting what is called the annuitization puzzle. 14 This is the notion that, despite theoretical models 15 predicting that retirees should allocate a large 16 percentage of their wealth into annuities, in many 17 practice, when you look at the outcome of annuity 18 markets in the developed world, you see the opposite 19 result. You see very low annuitization rates. If you 20 look at the prices, annuity prices seem particularly 21 high. 22 So the typical culprit for this outcome is 23 adverse selection leading to market unraveling. Chile 24 provides a really interesting counterpoint to this 25 experience. In Chile, around 70 percent of eligible</p>	212	<p>1 equilibrium that is quite similar to the observed 2 equilibrium in Chile. With the Chilean preferences 3 and the U.S. rules, you actually do get the U.S. 4 equilibrium of the full market unraveling, okay? 5 That's where we're going to go. Also, we are going to 6 compute welfare changes, and we are going to try to 7 compare welfare in both of these systems. 8 So the main take-aways that I want you guys to 9 have from this paper is, first, we are going to find 10 significantly more unobserved heterogeneity in the 11 type -- in the preferences for these retirement 12 products and significant correlation across the 13 different dimensions of this unobserved heterogeneity 14 than what has been posited by the previous literature. 15 Partly because of this, we can show actually 16 that when you reform the Chilean system to make it 17 more like the United States, you get something that 18 the previous literature hasn't been able to get, which 19 is full annuitization or close -- sorry, high 20 annuitization in Chile and full market unraveling in 21 the United States. 22 Having said that, the welfare implications are 23 ambiguous. It is not clear. So, in particular, even 24 though we can show that in the U.S. equilibrium, you 25 get market unraveling, it is not the case that the</p>

213	<p>1 Chilean equilibrium Pareto dominates the United States 2 equilibrium. There are people who are going to prefer 3 the United States system, and there are people who are 4 going to prefer the Chilean system. 5 Surprisingly, what we are going to find is that 6 individuals who have a low value for annuitization 7 prefer Chile to the United States, and individuals who 8 have high values for annuitization prefer the United 9 States to Chile, even though in the United States we 10 can have market unraveling. The reason for that is 11 because Social Security interacts with this market in 12 a very specific way but drives welfare, and I am going 13 to come back to that with more precision later on in 14 the presentation. 15 So I need to teach you a little bit about the 16 Chilean retirement system for anything that I'm going 17 to do now to make sense. I will try to be brief. So 18 Chileans save throughout their lives in private 19 retirement accounts. You may have seen many people in 20 this room, including myself, writing papers on this 21 savings market. That is not the market that we're 22 going to be studying today. Today we're going to 23 study the market of what happens once you retire and 24 you decide you want to access your money. 25 So to access this money, you are required by</p>	215	<p>1 withdrawal and an annuity is that under program 2 withdrawal, whatever money is remaining in your 3 account when you die is left to your heirs. So you 4 can immediately see where adverse selection is going 5 to come into this market. 6 If you are a 60-year-old, you have cancer, you 7 have a high probability of dying within the next ten 8 years, and you care about leaving money to your heirs, 9 you're just going to put your money in program 10 withdrawal, you are going to eat it until you die, and 11 your heirs will get the remaining. On the other hand, 12 if you expect to be long-lived, you have the incentive 13 to annuitize. 14 So I mentioned annuity contract types. Annuity 15 contracts here in Chile are quite sophisticated. They 16 can have deferral periods, meaning that we contract 17 today but they don't start paying out until d years in 18 the future. They can have guarantee periods, meaning 19 that we contract today, and if I die before the 20 guarantee period is over, the contract continues 21 paying out to my heirs. They can have up-front lump 22 sum amounts, they can have step functions, and 23 actually, you can mix everything I've said together. 24 So contracts can become quite, quite complicated. 25 So what are we going to be working with? We</p>
214	<p>1 law to go through an exchange. This exchange is 2 called SCOMP. The way it works is you go to an office 3 and you give SCOMP information about yourself, your 4 age, your gender, if you're married, the age and 5 gender of your spouse, how much money you saved during 6 your working life, and you tell SCOMP the types of 7 annuity contracts you would like to hear offers for. 8 I'll be more precise about what an annuity contract 9 type is in the next slide. 10 With this information and only this 11 information, SCOMP collates everything and sends it to 12 life insurance companies. Life insurance companies 13 then decide, person by person, contract type by 14 contract type, how much they are going to bid, okay? 15 That information gets sent back to SCOMP. SCOMP ranks 16 offers contract type by contract type, collates the 17 information, and sends it to retirees, who then decide 18 what they want to do. 19 The alternative to annuitization in this system 20 is an asset called program withdrawal. Program 21 withdrawal is basically a scheduled cake-eating 22 problem that is frontloaded relative to an annuity, so 23 you get more money right after you retire relative to 24 an annuity payout. 25 The second crucial difference between program</p>	216	<p>1 have an administrative data set of every single 2 individual who has retired in Chile between 2004 and 3 2013. We have everything life insurance companies see 4 about retirees and more; particularly, for example, we 5 know in which municipality they live, which life 6 insurance companies do not know. We see every offer 7 that is made in the system. We see every choice that 8 is being made. This is over 230,000 retirees and over 9 30 million annuity offers. 10 Moreover, we have been able to match this data 11 set to the administrative death records. So we are 12 able to tell, by 2015, whether these people are alive 13 or dead. And for the purposes of this talk, I am 14 going to focus on single life annuitants. If you're 15 interested in why we did that, we can talk about it 16 offline. 17 So there's a lot of descriptive work in the 18 paper which unfortunately I don't have the time to 19 talk about. I do want to hit the highlights, because 20 I think they set the stage for what we're going to do 21 next. 22 So, first, the market is very, very 23 unconcentrated. There's roughly 15 life insurance 24 companies making bids on people at any time. HHIs are 25 very, very, very low. As a result, markups are</p>

217	<p>1 partially -- as a result, when you compare the annuity 2 markups to the actuarial fair annuity, they're very, 3 very markups. Annuities are very competitively 4 priced. 5 There's vast heterogeneity in accepted contract 6 types. So it's not the case that people cluster on 7 taking one particular annuity contract versus the 8 others. I have motivated why this is. When there's 9 heterogenous preferences, there's going to be people 10 who are going to prefer contracts, for example, with 11 guarantee periods, because they expect to die and they 12 care about leaving money to their heirs, so on and so 13 forth. 14 Markups are low. There's adverse selection 15 into new annuitization. We can run the standard 16 Chiappori and Salani reverse selection test, and we 17 find what you would expect. People who buy annuities 18 live longer. 19 And in terms of exertion of market power or in 20 terms of exertion of brand preferences, roughly 20 21 percent of the population take what we call a 22 dominated offer. By that I mean they accept an offer 23 when there is another offer on the table that is the 24 same contract type and is more generous from a company 25 that has equal or better risk rating. Despite the</p>	219	<p>1 With this model, given a level of risk 2 aversion, given a level of wealth outside the system, 3 given a level of bequest motive, and given an 4 expectation about my own mortality, if I give you an 5 annuity contract offer or if I give you a program 6 withdrawal contract offer, I can calculate the optimal 7 consumption savings problem, I can solve the optimal 8 consumption savings problem, and I can recover the 9 value of that annuity contract. 10 The way to do that is numerically through the 11 endogenous grid method or the grid points method. 12 Sorry. So from now on I'm going to call a combination 13 of risk aversion, outside wealth, bequest motive, and 14 mortality shifter a type. And what we're going to do 15 in order to estimate demand is to take a grid over 16 this type space and solve the optimal consumption 17 savings problem for every point in the grid, for every 18 one of the 1.2 million offers that we see, okay? 19 Given a type and given a person, we are going 20 to impose or we are going to assume that the 21 individual accepts the offer that gives them the 22 highest utility from the optimal consumption savings 23 problem, and with that assumption, we are going to 24 solve for the distributions of types that rationalize 25 choice.</p>
218	<p>1 acceptance of dominated offers, the money people leave 2 on the table when they accept a dominated offer is 3 very, very, very low. 4 Okay. So what we're going to do in this paper 5 is we're interested in making comparisons across 6 contracts that have vastly different time properties 7 in terms of being financial assets. So to begin, they 8 have different flow payments over time. Second, they 9 have different exposures to risk, both longevity risk 10 and bankruptcy risk. And third, they have different 11 inheritance properties. 12 So the way we're going to do these comparisons 13 across these contracts, it's just really simple, and 14 it's to set up a finite horizon consumption savings 15 model. So the model is going to have the following 16 features: We are going to make a model that has 17 uncertainty over your own longevity and uncertainty 18 about whether the company that you are annuitizing 19 with is going to go bankrupt or not. It's going to 20 have a CRRA utility function to allow for the 21 possibility of risk aversion, and it's going to have 22 the potential for a bequest motive, and by that I mean 23 the potential for individuals to receive utility out 24 of leaving money after their death so that their heirs 25 can consume it, okay?</p>	220	<p>1 In this slide right here, then the problem of 2 solving for that distribution of types is in the 3 second set of equations. You can see that it's 4 actually a simple minimization of a constrained OLS 5 problem. π here is the probability that every 6 single -- associated to every single type. This is a 7 PMF. It must sum to one, and each of the elements 8 must have non-negative probability associated to them. 9 This may look familiar to you because this is 10 just Fox, Kim, Ryan, and Bajari. The only 11 contribution we have here is that we're marrying the 12 Fox, Kim, Ryan, and Bajari framework to an optimal 13 consumption savings model. Yeah. 14 So you may have some concerns about this model. 15 I'll point out the ones that I have. To begin, it's a 16 purely financial model, and what I mean by this is 17 that people are going to accept the offer that gives 18 them the highest utility. As a result, there is no 19 scope for brand preferences. One of my advisors was 20 fond of calling this the Snoopy effect because one of 21 the companies in the system was Met Life. So the idea 22 was perhaps you like Snoopy and, as a result, you are 23 willing to accept a lower offer from Met Life than you 24 would from another company just because you like the 25 brand. We are ruling that out. I'm comfortable</p>

221	<p>1 ruling it out, to be honest with you, because even 2 when we see the acceptance of dominated offers, the 3 amount of money that is being left on the table is 4 rather low, but that is an assumption. 5 Second, there could be information revelation 6 in the request stage, and by that I mean when you 7 elicit contract offers, the contract menu that you are 8 requesting could tell insurance companies information 9 about your own immortality. If that is the case, we 10 are ruling it out. It would bake in correlation 11 between the choice set and your own distribution of 12 types, similar to what Matt talked about in the 13 previous presentation. 14 To alleviate that concern, we're working on 15 re-estimating the model conditional on the request set 16 so that within the request set there is no 17 heterogeneity and no information revelation. The 18 hairy thing here is going to be finding a group, a 19 mass of consumers, that all request exactly the same 20 contract so we can run this. 21 You may think that there is heterogeneity in 22 distribution of types across observables; for example, 23 it might seem insane to estimate this model jointly 24 for men and women. We agree. We're separating out 25 across genders, and we're also separating out across</p>	223	<p>1 That's the only way we are going to be able to recover 2 the distribution of types. 3 Let me give you an example of when that breaks 4 down. Risk-neutral individuals do not choose over 5 lotteries taking into account their outside wealth. 6 So for the risk-neutral types, we, of course, cannot 7 recover the distribution of outside wealth. Despite 8 that, I think that this works rather well, in 9 particular because the choices here that people have 10 over these different -- what you could think about as 11 lotteries -- are quite stark. 12 For example, an individual who is illiquid upon 13 retirement and who expects to live for a very short 14 time will never take a deferred contract even if the 15 deferred contract is quite generous just because they 16 won't live long enough to recoup the investment of not 17 being paid for a certain number of years. 18 As another example, someone who cares 19 absolutely nothing about leaving money to their heirs 20 will never take a contract with a guarantee period, 21 because a guarantee period only shifts down the 22 payments you get over your life at the benefit of 23 leaving money to your heirs. 24 Okay. So the unfortunate thing about these 25 grid estimators is that the result of the estimation</p>
222	<p>1 pension savings quartiles. So we're going to estimate 2 this model for every gender/pension savings quartile 3 pair separately. 4 And second and finally, those of you who have 5 worked with these types of estimators may have 6 experience that they can be quite finicky and 7 sensitive in terms of the grid that you are choosing. 8 We're trying to be very careful about the choice of 9 grid and trying to pick it in a smart way so that this 10 is robust. I, unfortunately, don't have the time to 11 delve into that, but I'm happy to talk about it 12 offline with you if you are concerned about that. 13 So a key question that you might be thinking 14 now is, how can you identify these distribution of 15 types just using the choice data? And from a formal 16 perspective, what you need is -- in the previous 17 slide, we had this S matrix, which is simply a matrix 18 that has, in every row, individuals and offers, and in 19 every column, it has types. This S matrix is going to 20 have zeros and ones, a one when a type chooses a 21 contract and a zero when a type does not choose a 22 contract, and formally what you need for 23 identification is invertibility of S-prime-S. Now, 24 what does that mean in practice? It means that 25 different types have to make different choices.</p>	224	<p>1 routine is a list of types with different weights, 2 which makes it hard for presenting. The list of types 3 and weights for every single quartile gender is in the 4 paper. I'm just going to talk about the highlights. 5 So the first thing that we found very 6 interesting is that there's a large, significant 7 heterogeneity in bequest motive -- there's actually 8 bimodality in bequest motive -- and that an intuitive 9 result, we're finding bequest motives are higher for 10 women than for men. This is consistent with findings 11 in the development economics literature as well. 12 We're finding a large heterogeneity in 13 mortality expectations relative to the table, that's 14 the Chilean death table; that is, individuals are not 15 discounting the future as if they expect to die 16 according to the Chilean death table. There's people 17 who expect to be sicker and there's people who expect 18 to be healthier than the Chilean death table. Poorer 19 individuals across the board seem to have higher 20 mortality probabilities. 21 We're finding that the distribution of outside 22 wealth that we are backing out shifts to the right as 23 pension balances increase. We're finding low 24 heterogeneity in risk aversion, significantly lower 25 values than the literature, and we're finding</p>

225	<p>1 mortality probabilities that are negatively correlated 2 with bequest motives and that are negatively 3 correlated with risk aversion. This is really 4 important. 5 In a standard adverse selection market where 6 the only source of private information is just 7 mortality, the first people who annuitize are going to 8 be the people who expect to be the longest lived. The 9 last people to annuitize are going to be the people 10 who expect to be the shortest lived. That creates the 11 standard increasing average cost curve result. 12 Here, it doesn't have to go that way. It could 13 be the case that the first people who annuitize 14 actually aren't the people who are the longest lived, 15 and I'll show you how that happens and when that 16 happens. 17 So the remainder of the talk, I am going to 18 start actually applying these results. So the first 19 thing I am going to do is I am going to simulate 20 market equilibria under stripped-down, simple versions 21 of the Chilean and the U.S. institutional framework. 22 My goal here is going to be to highlight the change in 23 the demand in the actual cost curve that's induced by 24 the introduction of Social Security. 25 In both Chile and in the U.S. -- and in</p>	227	<p>1 taken away from you and returned to you immediately in 2 an actuarially fair annuity. It's just that you have 3 no choice over this matter. The remainder of your 4 money can be either allocated into an annuity or it 5 can be withdrawn lump sum, okay? 6 So with that we can start looking at the 7 equilibrium for both Chile and the United States. I'm 8 going to show you results for females in the second 9 quartile, because it's actually the results that are 10 the most stark. You can see the other genders and the 11 other quartiles in the data. The main conclusions 12 we're going to see at the back end of the paper 13 actually are not going to matter at all. 14 Okay. So the green line here is the demand 15 function. The red line here is the average cost 16 curve. Why is demand upward sloping? This is just 17 the standard annuity thing. On the X axis, I have the 18 wealth annuitized. On the Y axis, I have the 19 generosity of the annuity. As the annuity gets more 20 and more and more and more generous, of course, more 21 people are going to annuitize. That's why the shape 22 looks like that, okay? 23 The average cost curve, you can just think 24 about it very simply as the highest annuity offer that 25 a company can make given the annuitant population and</p>
226	<p>1 everything you are going to see now, I am going to 2 assume that there is a single annuity contract, zero 3 guarantee, zero deferral period, and I am going to 4 assume that the market is perfectly competitive, and I 5 am going to assume, just like it is the case in Chile, 6 that pricing is on gender and on pension balances. 7 I'm going to allow for the possibility of 8 fractional annuitization, and by that I mean that 9 individuals don't have to allocate their full wealth 10 to either an annuity or to the alternative but, 11 rather, they can allocate fractions of the wealth to 12 both retirement assets. 13 And I'm going to assume that there's a 1 14 percent bankruptcy probability in the world where you 15 annuitize. This is mostly to bake into the model the 16 feature of the United States system where we take a 17 private annuity and the company goes bankrupt, you're 18 out of luck. The results that you're going to see now 19 actually don't change if you change from 1 percent to 20 0 percent. 21 In Chile, the alternative to annuitization will 22 be this program withdrawal problem that I told you 23 before. In the United States, I'm going to follow 24 Mitchell Perturba (phonetic) and co-authors in 25 assuming that 50 percent of your pension savings are</p>	228	<p>1 still break even, okay? In a world where the only 2 source of selection into annuitization is 3 heterogeneity and mortality, the first people to 4 annuitize are going to be the longest lived; the last 5 people who annuitize are going to be the shortest 6 lived. As a result, the offer you can make and still 7 break even is going to be increasing as a function of 8 the amount annuitized. 9 Here you see, in fact, that for some regions of 10 our actual cost curve, the curve is, in fact, 11 decreasing, not increasing, suggesting advantageous 12 selection. Despite that, when you compare the 13 equilibrium here, represented by the blue dot, the 14 annuity rate that you see in equilibrium is, in fact, 15 lower than the actuarially fair annuity. So the 16 advantageous selection is just loke (phonetic), okay? 17 And we're getting an annuity rate in the simplified 18 version of Chile of roughly 55 percent annuitization. 19 I should apologize and say that nothing here has 20 standard errors. We're working on those, and my 21 apologies for that. 22 Here's the U.S. equilibrium. So, again, the 23 green line, demand, the red line, average cost. There 24 is no intersection. Full market unraveling. To be 25 honest with you, once you add standard errors,</p>

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1 probably there will be an intersection between zero
2 and 10 percent annuitization. Materially, the
3 conclusions that we are going to reach are not going
4 to change.

5 So you can see that there is a large
6 contraction and rotation of the demand curve when you
7 introduce 50 percent Social Security. Why is that?
8 Because now, very intuitively, every single person in
9 the market already has half their wealth in an
10 annuity. As a result, the willingness to pay for the
11 marginal annuity dollar, of course, has to fall.
12 That's the contraction in the demand curve.

13 The rotation in the demand curve comes from a
14 homogenization of risk across individuals induced by
15 setting such a high floor. Actually, the average cost
16 curve doesn't change that much. I'm happy to talk
17 about that offline. So here we get full market
18 unraveling.

19 Okay. Now, 50 percent is just a number that
20 Jim and Olivia picked. You could play around with
21 other numbers and see whether this result is robust or
22 not. So in this plot, I am showing you on the Y axis
23 the fraction of wealth that is annuitizing when you
24 move the amount of money in Social Security from 0
25 percent in Social Security, where the only difference

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1 between Chile and the U.S. is lump sum versus program
2 withdrawal, and 90 percent of your money in Social
3 Security.

4 So you can see that for around 50 percent of
5 your money in Social Security and above, you are
6 getting the market unraveling result. For values of
7 money in Social Security below that, that is not the
8 case, okay?

9 Now, up to now, I've tried to make no
10 statements about welfare. You may be thinking that
11 market unraveling should have an adverse welfare
12 effect, in particular for people who value
13 annuitization. In fact, we're finding that the story
14 is not as simple as that. So we've calculated type by
15 type and amount in Social Security by amount in Social
16 Security the compensating variation that would leave
17 an individual indifferent between being in the United
18 States and being in Chile. Positive numbers here are
19 people who have to be paid in the United States to be
20 indifferent between the United States and Chile.
21 Negative numbers are the converse, okay?

22 So the main take-away from these plots is that
23 in none of these cases it is true that one system
24 Pareto dominates the other, okay? There are always
25 going to be people who prefer the Chilean system, and

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1 there are always going to be people who prefer the
2 United States system.

3 I have a minute. I'd like to characterize
4 these types, so I'll be brief about that. What we
5 find is that individuals who fully take up program
6 withdrawal in Chile dislike the United States system.
7 We are going to call these people people who have low
8 values for annuitization. The reason is quite
9 intuitive. These people are being forced to annuitize
10 a significant portion of their wealth even though, for
11 example, they're going to die two years from now and
12 they really care about leaving money to their heirs.

13 They do not enjoy the benefits of the Social
14 Security annuity, and as a result, when you move to
15 Chile and you let them put their money in an asset
16 where, upon death, their heirs are going to get
17 something, of course, their welfare is going to be
18 higher.

19 On the other hand, people who greatly value
20 annuitization systematically prefer the United States
21 to Chile, and this was surprising to us because we
22 expected that when the market unravelled, that wasn't
23 going to be the case. The reason why this happens is
24 actually simple. For levels of Social Security where
25 the market doesn't unravel, putting all your money in

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1 an annuity in the United States has a higher return
2 than putting all your money in an annuity in Chile,
3 so, of course, these people prefer the United States
4 to Chile.

5 When Social Security is so high that the
6 private annuity market unravels, well, Social Security
7 is so high that you're already getting the Social
8 Security annuity for a vast portion of your wealth.
9 The remaining dollars are the dollars that you cannot
10 annuitize, and for those marginal dollars, the
11 difference between annuitization and lump sum
12 withdrawal is not as large as for the inframarginal
13 dollars. As a result, even though their welfare does
14 decrease relative to cases where Social Security has
15 lower coverage, in fact, the United States for these
16 types still dominates Chile.

17 Okay. So we've estimated this model of demand.
18 We've started playing around with the institutional
19 setup. The key take-aways that I want you to come up
20 with is that, like predicted, when you introduce
21 Social Security, you are going to get a contraction in
22 the rotation of the annuity demand function. We do
23 get market unraveling, like you see in the developed
24 world.

25 Despite this, the Chilean system does not

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1 dominate, and in particular, high-value annuitization
2 types are not worse off in the United States. The
3 people who actually prefer Chile are people who we
4 think haven't been thought about too much. It's
5 people who reach 60 or 65 years old, and they're sick,
6 they're going to die soon, and they're not going to
7 enjoy the benefits of the Social Security annuity.
8 We're starting to think about policies that
9 potentially could benefit these types.

10 So, thanks.
11 (Applause.)

12 MR. PETEK: So J.F. will discuss Gaston and
13 Manisha's paper.

14 MR. HOUDE: Okay. Thank you very much for
15 having me to discuss this paper. Let me just start by
16 saying this is a great paper, very ambitious, and this
17 is actually a great example of a -- you know, a very
18 tiptop IO paper, uses very good IO techniques to
19 estimate, you know, of course, an empirical paper on a
20 great empirical public finance question that we should
21 care about. So it's not -- maybe not the, you know,
22 perfect paper for this audience, but I think the paper
23 is going to have a great future, because, you know,
24 the question is really important.

25 Now, what is the paper doing? So let me just

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1 briefly give you a short overview of the question. I
2 am going to give you a very broad overview of what the
3 paper is doing. So the paper estimates a life cycle
4 model of consumption savings with adverse selection.
5 I put in parentheses "advantageous selection" because,
6 you know, it does play a role, because the model is
7 rich. It does have, you know, a fairly rich model of
8 correlation types, and though for some segments it
9 does have advantageous selection and then applies it
10 to the Chilean annuity retirement savings system.

11 Now, what's different? So I am really not a
12 specialist in the U.S. security -- Social Security
13 system, but what's different about Chile versus the
14 U.S. is these two things. So, first, when you have to
15 retire, you choose between -- essentially you're
16 offered this menu, which is a competitive exchange,
17 where you have these companies offering you these
18 products, who are bidding for your contract, and this
19 is actually a very competitive market, which, you
20 know, as Gaston showed -- and I am going to give you
21 the example in the next slide -- the prices are very
22 competitive, and consumers have these menus that, you
23 know, great for them.

24 And relative to the U.S., the other big
25 difference -- and this is where the results come

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1 from -- is that unlike the U.S., consumers have the
2 option of moving all of their savings to this private
3 security market. They also have a public option if
4 they don't want to, so this PW option, but unlike the
5 U.S., we do allow these retirees to use all their
6 savings and put them in this type of annuity. So it
7 increase the market size quite a bit, which
8 essentially solves a lot of the adverse selection
9 problem, and as a result, we do have a much higher
10 takeup rate than the U.S.

11 Now, the richest question is, as Gaston put it,
12 you know, what would happen if we subject the poor
13 Chilean to the U.S. and will the market unravel, and
14 the answer is mostly yes, and, of course, as I said,
15 this is a really important question, because, you
16 know, we are stuck with that problem here in the U.S.
17 We do have the problem of how do we fund the Social
18 Security system in the U.S., and this is a good step
19 in answering that question.

20 Okay. So this is not a great scan from the
21 paper, but this is what the -- you know, hopefully the
22 people in Chile see better. So basically what you do
23 see when you retire is you see this set of bids and --
24 well, first of all, there is two things that I was
25 personally surprised, is, well, first of all, you have

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1 quite a bit of competition, and these prices are
2 individualized prices. There's, you know, full price
3 discrimination, potentially, but there's not a lot of
4 price dispersion.

5 Now, you don't see it here, but there's -- you
6 know, the range of prices is very narrow. If you take
7 out the outlier at the bottom, you know, the range of
8 price is about 2 1/2 percent, at least in this table.
9 I don't know how representative that table is, but,
10 you know, more or less, you know, we're not far from
11 the LIBOR price, you know, essentially.

12 And a part of that dispersion is explained by
13 the riskiness of these life insurance companies, but,
14 you know, more or less, you know, this is pretty much
15 one price. And then price means the payment, and then
16 if you take in the markup that these guys are
17 receiving, if you take out the very rich and the very
18 poor, you know, it's pretty much constant markup,
19 okay?

20 So, you know, the paper talks a little bit --
21 so I thought I should include a little bit of that
22 since this is an IO conference. You know, this paper
23 talks a little bit about this has evidence of price
24 discrimination. This is -- you know, maybe I was
25 thinking about this weird, but this is -- you know,

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1 this is not -- this is sort of the opposite of price
2 discrimination in some sense because the poor are
3 priced -- are getting a higher markup than the rich,
4 and so we think that the poor have more price -- are
5 more price-sensitive, but I think the reason this is
6 not price discrimination is because the poor --
7 there's really no -- there's not a lot of competition
8 for the poor in this market, and that's really what's
9 going on at the bottom of the distribution, which
10 actually, one thing in the next iteration of the
11 paper, we might want to exclude these guys at the
12 bottom, because it does generate a lot of random
13 variation in prices, which might violate some of --
14 you know, when we talk about these guys taking up
15 weird offers, you know, maybe that's coming from the
16 bottom of the distribution. So that might be one
17 thing that can explain this.

18 The other thing is that the paper mentioned
19 that a little bit -- so, these guys sometimes use
20 agents to shop. Sometimes they shop on their own.
21 They also have an option of renegotiating these
22 offers. And the paper says, well, they don't
23 negotiate that much. They barely negotiated by 2
24 percent on average. Well, 2 percent is the range in
25 this table, so that will eliminate more or less the

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1 mispricing that we have when people take dominated
2 offers. So it would be nice to know a little bit more
3 what's happening with these agents and the
4 renegotiation.

5 And the flip of the markup is also if you
6 charge very high price, people are not going to take
7 these offers, and so these low guys, these low wealthy
8 guys are not going to take those offers. But the
9 other thing that is weird is why is it that the
10 wealthy guys are not taking these really good offers?
11 So this is one thing I was a bit puzzled when I saw
12 this table. Why is it that the wealthy guys were
13 actually receiving offers with negative markup and not
14 taking those offers?

15 Okay. So, again, I was not the right audience
16 for understanding annuity markets in general, although
17 I really cared about the question, so let me -- so it
18 took me a little bit of time to understand why demand
19 was upward sloping. I might have been very tired,
20 that's also part of the problem, but, you know, at the
21 end of -- and the paper is very clear in terms of, you
22 know, how things work.

23 Now, what was going on here is that, you know,
24 the governmental option, essentially the payments are
25 decreasing, so people who are going to take the

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1 governmental options is only people who expect to die
2 very soon, okay? And so people who are going to take
3 the annuity are people who expect to live very long.
4 And from the point of view of the life insurance
5 companies, these are the risky people, and so that's
6 the adverse selection problem. So people who are
7 buying the annuity are people who expect to live
8 longer than their age suggests, okay? And that's the
9 problem.

10 So you can -- basically the way Gaston
11 construct this willingness-to-pay curve, because the
12 model is actually -- is complicated, right? So it's
13 not that trivial to figure out what is an indifferent
14 consumer given the nonlinearity. So he's constructing
15 this indifference point, you know, what is my
16 riskiness such that my -- I'm indifferent between
17 these two contracts, and then I can raise the price of
18 the contract, and then I figure out what is my
19 riskiness so that I'm indifferent. And as they raise
20 the offer, I get different levels of riskiness.

21 And so as you go -- as you try to raise the
22 contract, you get kind of people who expect to live
23 shorter, less risky individuals. So, okay, so this --
24 again, so this is -- you know, I'm not in this
25 literature. I was very surprised that there was a

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1 corner of the econometrics literature that was
2 thinking about upward sloping demand curve still, but
3 anyway, that was just a small comment.

4 The U.S., though, so the U.S. -- I think this
5 is -- you know, the most interesting part of the
6 paper, is, you know, what -- how do we think about the
7 U.S. Social Security system in this context, and it's
8 very intuitive, and Gaston explained it very well, is
9 that it is both the rotation and the contraction of
10 the demand, because we're essentially insuring a lot
11 of the risk by telling you, well, 50 percent of your
12 savings is going to be automatically annuitized, and
13 so there's less of a need to annuitize the remainder,
14 and so people are willing to pay less. So there's
15 just less demand for it.

16 Now, I was reading the draft and I couldn't
17 figure out why the points were moving left, so that's
18 a small point, but it would be nice, since there's
19 actually quite a bit of advantageous selection in some
20 of these segments, to understand, well, if there's
21 advantageous selection in the U.S. market, well, how
22 does this work in this market? So Gaston mentioned
23 that the cost curve should not change too much, but in
24 the simulation, it does change a little bit. So I
25 couldn't really understand everything about that.

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1 Now, let's talk about the structural model a
2 little bit. So the structural model is more
3 complicated in its pictures because it has four
4 dimensions of heterogeneity. So it's not just my
5 mortality risk. It's my risk aversion, it's how much
6 I care about my kids, and the initial wealth. So
7 there's four dimensions. All these dimensions are
8 allowed to be correlated. So it's a very rich model.

9 So Gaston used this finite mixture approach to
10 estimate that. So one thing that I was not clear --
11 and in the presentation it was more clear -- was how
12 observed heterogeneity is accounted for, and so that's
13 clear now because everything is estimated separately
14 for male and female, but in practice, there is more
15 observed heterogeneity than that.

16 Now, this is a quote from the paper. You know,
17 what -- the one thing that -- and I'm more of a
18 parameter guy. I kind of like the normal model, but,
19 you know, when you look at the identification of these
20 models, what's difficult is it is very black boxy,
21 right? So the model is identified because it's
22 identified, because the rent condition is satisfied,
23 and so you lack a little bit of the link between the
24 data or the reduced form and the parameters. What
25 is -- you know, that's lacking a little bit. And

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1 since these correlations are so important, it would be
2 important if that would be sketched out a little bit.

3 So I have a comment on the next slide, but one
4 thing that would help here is to maybe estimate a
5 version of the model that would fit a little bit
6 closer to the literature, like the Cohen and Einav
7 type paper, that it uses parameteric model.

8 Now, finally, about -- this is an IO
9 conference, so I have to talk about the endogenous
10 prices. I do believe that market is competitive, but
11 people do pay different prices, and they do accept
12 rejected -- the dominated offers. So there's some
13 room for endogeneity here.

14 So you talked about brand preferences, so
15 that's one reason why that could be. Another reason
16 is the fact that these offers are sometimes
17 renegotiated. So think about the case of two guys in
18 the deal who look up servicing equivalent who accepted
19 different offers. Well, if I saw different offers in
20 the data, the model is going to say, well, we have
21 different unobserved taste, but it could be that the
22 price is measured with error, because we renegotiated
23 those prices. And so that might be one thing.

24 And that that could be, you know, one source of
25 simultaneity, and so that would be one way of

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1 correcting -- so I have one suggestion there, and this
2 is where understanding a little bit better the role of
3 the agent would help. And then the other suggestion
4 was related to the identification. So one way of
5 talking about identification a little bit is through
6 these adverse selection tests. So the shepherd, the
7 Chiappori and Salani is a test of adverse selection.

8 Well, you know, it is -- if you pass the test
9 of adverse selection, it does tell you that there is
10 an observed heterogeneity, so if you find advantageous
11 selection, like we do in the paper, that means that
12 for some consumers we should be able to find the
13 opposite correlation, and so we should be able to find
14 that in the reduced form as well. So there should be
15 a tighter link between the structural model and the
16 reduced form, and that would help in understanding the
17 results.

18 Okay, I think I am out of time. Thank you very
19 much.

20 (Applause.)

21 MR. PETEK: So we just have time for a couple
22 questions.

23 MR. BESANKO: So my impression is that a lot of
24 the countries that have private account systems have a
25 minimum pension guarantee. So if you don't save

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1 enough over your life, you're guaranteed a certain
2 amount. Now, that sounds Social Security-like. I
3 don't know if Chile has that, but if so, did you look
4 at that, and how did that factor into your work?

5 MR. ILLANES: Yes, yes. So, thank you. This
6 is something that I do talk about in the longer format
7 presentation but I can't touch in 25 minutes.

8 In the background of everything here, there is
9 a minimum pension guarantee. On the first slide, why
10 I say 70 percent of eligible annuitants accept an
11 annuity offer, it's because if you cannot fund an
12 annuity offer that falls above the minimum pension
13 guarantee, you are not eligible to annuitize in Chile.
14 You are not in this market. You must take program
15 withdrawal. Those people are not in my sample.
16 That's why I have 230,000 retirees over eight years,
17 which may seem like a small number to you.

18 So if you are poor enough, you are not in this
19 market. Those are the eligible people. If you take
20 an annuity, it must be above the minimum pension
21 guarantee, so that's it. If you take program
22 withdrawal, when your money falls sufficiently low
23 such that you are below the minimum pension guarantee,
24 the Government begins to top up program withdrawal,
25 essentially subsidizing you.

245	<p>1 That's in the model. It's in the estimation. 2 We're controlling for that, and it's one of the 3 observables that enters person by person into the 4 national consumption savings model, but, yeah, it's 5 something that I can't talk about in 25 minutes. 6 AUDIENCE MEMBER: So I have a couple of 7 questions. The first one is, do you actually see a 8 firm in your sample offering a menu of options to a 9 consumer? 10 And then the second question is somewhat 11 related. So are you worried that the consumer may 12 actually misreport their savings balance so that they 13 can actually get a better price? 14 MR. ILLANES: Thank you. So most firms bid for 15 every single contract type, okay? So it tends to be 16 the case that if a firm is bidding for you, it's 17 bidding for you on every contract that you elicited 18 offers for, okay? So from that perspective, the 19 common thing is to see the menu. 20 Regarding misreporting, there can be no 21 misreporting. The way this works is that the 22 Centralized Exchange actually pulls the records from 23 the savings period and sends them directly to the life 24 insurance companies. So from that perspective, there 25 is truthful reporting so that that can't happen.</p>	247	<p>1 contract that they would like more, that will not lead 2 to higher expenses for the Social Security 3 Administration. 4 And I can't comment on whether that's going to 5 work out, but we suspect that if you can come up, for 6 example, with a program withdrawal alternative that is 7 sufficiently not attractive, so annuitization -- so 8 people who like Social Security stay in Social 9 Security, but it is sufficiently attractive for people 10 who really dislike annuities to leave the Social 11 Security annuity and convert it into program 12 withdrawal, maybe there's a way to achieve that goal. 13 But that's something that we're working on, and I 14 don't know yet. 15 MR. PETEK: Okay, thank you. 16 (Applause.) 17 MR. PETEK: We will take a break until 4:30 and 18 come back with Ali's keynote. 19 (End of session.) 20 21 22 23 24 25</p>
246	<p>1 Yeah. 2 MS. JIN: This is an interesting paper. You 3 focus on individual choice of contracts. If we 4 shifted gear to, say, the program designer, the 5 Government in the U.S., at least, by offering Social 6 Security, U.S. Government is functioning like an 7 insurer here. So I wonder from that perspective what 8 implication would your results have in terms of, say, 9 the risk that Social Security Administration is taking 10 in terms of insolvency versus kind of privatize all 11 the Social Security money into individual accounts? 12 MR. ILLANES: Yeah, so let me touch on the only 13 part of Social Security that our paper can talk about, 14 which is what happens when you're taking money out. I 15 don't want to talk about how people should feel about 16 when they're putting money into Social Security and 17 what they should think about when they're 20 years 18 old, because that's not our paper. 19 From the perspective of what happens once 20 you're 60 or once you're 65 and you're deciding to 21 retire, you want to withdraw money, our main finding 22 is that there are going to be people who are really 23 going to dislike this contract, right? And what we're 24 trying to work on now is to try to determine, if for 25 those people we could offer them an alternative</p>	248	<p>1 KEYNOTE ADDRESS: 2 SEARCH, ASYMMETRIC INFORMATION, AND COMPETITION 3 MR. PETEK: All right, let's get started again. 4 All right, so Ali Hortaçsu is going to give our 5 second keynote address, "Search, Asymmetric 6 Information, and Competition." He is the Ralph and 7 Mary and Otis Isham Professor of Economics at the 8 University of Chicago. He's also a member of the 9 American Academy of Arts & Sciences, a fellow of the 10 Econometric Society, and a fellow of the National 11 Bureau of Economic Research. His recent research has 12 focused on industrial organization, auctions, search 13 and matching models, production, and financial 14 networks, with applications in finance, energy 15 markets, and the internet. 16 Ali? 17 MR. HORTACSU: Thanks a lot, David, and thank 18 you so much to the organizers for having me on the 19 program to provide some input. Thanks again for, you 20 know, putting together this program, and, you know, 21 sort of in the first half of the program, I saw a lot 22 of Stigler 1964, so this is more -- in the afternoon, 23 we switched over to more Stigler 1961, to search 24 models, so we're -- and it was great to see, you know, 25 in the previous session, we had a lot about search,</p>

249	<p>1 but, you know, is it about search, about bargaining?</p> <p>2 The second paper was a financial products</p> <p>3 market, and actually I was asking around. I'm sorry,</p> <p>4 I'm like woefully ignorant about where the</p> <p>5 jurisdiction of the FTC is, you know, do you guys work</p> <p>6 with financial products markets at all? You know, I'm</p> <p>7 not so sure, but I do think these are important</p> <p>8 markets to study.</p> <p>9 You know, to study this, you know, this is</p> <p>10 probably sort of the longest list of co-authors I have</p> <p>11 written a paper with, but, you know, everybody</p> <p>12 contributed in very important ways -- except myself,</p> <p>13 we'll see -- and so this is joint work with Sumit</p> <p>14 Agrawal, John Grisby -- who is going to be a very</p> <p>15 promising job market candidate, maybe not this year</p> <p>16 but next year -- so my former colleague, Gregor</p> <p>17 Matvos, Amit Seru, and Vincent Yao.</p> <p>18 So to talk about Stigler 1961, diagnostic for</p> <p>19 some sort of funniness business going on in the market</p> <p>20 is price dispersion, and mortgages seemed to fit that</p> <p>21 bill, at least from a prima facie point of view. This</p> <p>22 is a plot I have from a paper by Amit and Gregor and</p> <p>23 their co-author, Umit Gurun, on subprime mortgages.</p> <p>24 So they found, after residualizing a lot of</p> <p>25 demographic information, et cetera, on rates, mortgage</p>	251	<p>1 see posted rates, but, you know, posted rates might</p> <p>2 not mean anything.</p> <p>3 You have to put in an application, and they</p> <p>4 have to check your credit and see if -- you know, what</p> <p>5 rate you qualify for. So it takes a while. There's a</p> <p>6 cost to actually getting that quote from somebody,</p> <p>7 with, like, insurance as well.</p> <p>8 And then you -- and then what causes this sort</p> <p>9 of price dispersion, Andrew in a comment earlier said,</p> <p>10 you know, the sophisticated naive decompositions,</p> <p>11 right? So the sophisticated consumers, you know, easy</p> <p>12 to search, they have information, but nonsophisticated</p> <p>13 consumers, they just don't know.</p> <p>14 In some very nice models, like the Varium</p> <p>15 (phonetic) model, they just take the price or they do</p> <p>16 very little search. And this has become, you know,</p> <p>17 for better or worse a very attractive framework in</p> <p>18 consumer finance, precisely because in this type of</p> <p>19 market, you know, information is relatively hard to</p> <p>20 get, plus, you know, a huge area of products.</p> <p>21 Gaston talked about the very large array of</p> <p>22 contracts that people have to sort through, and</p> <p>23 they're complex. You know, when you get the mortgage</p> <p>24 product, what you're buying is the contract you</p> <p>25 signed. I don't know how many in this audience who</p>
250	<p>1 rates for the same type of contract, you know, you can</p> <p>2 see the X axis, the horizontal axis in terms of</p> <p>3 percentage points, big dispersion.</p> <p>4 What we're going to start off with in this</p> <p>5 paper, in this project, is not the subprime but</p> <p>6 conforming mortgages. These are things, you know,</p> <p>7 basically Fannie and Freddie, sort of these government</p> <p>8 entities insure more plain, vanilla contracts with</p> <p>9 more risk, with higher credit borrowers, still a</p> <p>10 pretty large residualized dispersion, you know,</p> <p>11 people, you know, on order of percentage point,</p> <p>12 interquartile, and the distance here -- and it's not</p> <p>13 just in the U.S.</p> <p>14 J.F., with Jason Allen and Rob Clark, has, you</p> <p>15 know, two very nice papers on the Canadian mortgage</p> <p>16 market that really inspired us to write this paper.</p> <p>17 They note large dispersions in the Canadian</p> <p>18 residential mortgage market as well, both residualized</p> <p>19 and nonresidualized.</p> <p>20 So since 1961, right, so to explain this, one</p> <p>21 of the main drivers is information, you know, George</p> <p>22 Stigler puts it much better, sort of, you know,</p> <p>23 there's power in information, right? So if you --</p> <p>24 really, consumers don't see all the prices, especially</p> <p>25 in, you know, a market like mortgages, where you can</p>	252	<p>1 got a contract actually read through all of those</p> <p>2 pages, you know, probably not, you know -- maybe a</p> <p>3 few, but -- and infrequent transactions, okay?</p> <p>4 So -- and then -- and we talk about, you know,</p> <p>5 why people pay different prices, you know, who pays</p> <p>6 more, sophisticated -- who pays more? Are these</p> <p>7 unsophisticated people or sophisticated people, et</p> <p>8 cetera? And we have different -- and this leads to a</p> <p>9 lot of justifications for interventionism, especially</p> <p>10 from regulatory agencies, right? So we want to</p> <p>11 protect especially the vulnerable population of</p> <p>12 consumers from making bad choices, and, you know, we</p> <p>13 want to help prevent firms from exploiting naive</p> <p>14 consumers.</p> <p>15 And a lot of these interventions are in the</p> <p>16 form of, you know, information treatments, in the</p> <p>17 sense of, you know, mandated disclosure of certain</p> <p>18 things, you know, putting prices up on, you know, web</p> <p>19 pages, you know, that everybody can access or, you</p> <p>20 know, plain sort of things like interest rate</p> <p>21 ceilings.</p> <p>22 And just to preview, I have a very good student</p> <p>23 this year on the market to talk about interest rate</p> <p>24 ceilings, to advertise for him, you know, some policy</p> <p>25 interventions that go from very coarse to, you know,</p>

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1 rather subtle ones, okay?
 2 But a lot of this intuition comes from our
 3 understanding of what I'm going to call standard
 4 product markets. Standard product markets, the
 5 buyer's payoff depends on the price. The seller's
 6 payoff depends on the price, right? But credit
 7 products are somewhat different, and Gaston's paper
 8 was on adverse selection in the annuities market.
 9 This is a market where, you know, the borrower cares
 10 about essentially only the price. They might care
 11 about Snoopy, but -- you know, probably they
 12 shouldn't -- but the lenders definitely depend on who
 13 signs the contract, right?
 14 Is it -- you know, aside from the rate you get,
 15 right? So is this person going to repay the loan or
 16 is this person going to, you know, pay it back way too
 17 early, and is there a repayment risk in this thing?
 18 So the lenders are going to screen. They are going to
 19 get a lot of information, decide whether to accept or
 20 reject applicants, and they put a lot of resources
 21 into this.
 22 And I would like to say sort of a main, you
 23 know, let's say thrust of this paper is to sort of
 24 motivate that the screening aspect is very important
 25 in these markets, and I would like to -- we haven't

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1 done it yet, but follow it on with other work, you
 2 know, trying to get at the importance of screening
 3 technology in these markets, especially in these days
 4 with -- you know, when people talk about big data and
 5 how this interacts with it, I think it's an important
 6 question.
 7 So to get at this, we have a very nice data
 8 set -- although I keep hearing from people that even
 9 nicer data sets are coming online, so we should hurry
 10 up and try to publish this paper before the young
 11 people, you know, publish their papers faster than we
 12 do.
 13 So we get -- there's essentially two separate
 14 data sets. We have data on mortgage applications, so
 15 we have all the information they filled out on those
 16 application forms and the decision, whether this was
 17 accepted or rejected for a mortgage, and we also have
 18 data on granted mortgages, the mortgages in the
 19 marketplace.
 20 So the main, I guess, fact that I'm going to
 21 say -- and there's a few different figures that are
 22 going to say the same picture -- but here higher
 23 search interest intensity is going to be correlated
 24 with higher interest rates that people get,
 25 conditional on many observables, you know, controlled

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1 for. Of course, a standard product market model where
 2 there's no screening, you would expect people who are
 3 searching more to be the more sophisticated consumers,
 4 that lower search costs, they should be able to find
 5 lower interest rates, but in this market, even if you
 6 control for a lot of observables, those who are
 7 searching more seem to be getting higher rates.
 8 And you might say, well, you know, why is that?
 9 Well, you know, it's not difficult. The answer is
 10 because, you know, there's screening, and screening is
 11 informative. Lenders screen, and even conditional on
 12 the observables, it seems like they are -- you know,
 13 that they are rejecting people differentially, you
 14 know, given our data sets, and the people who are
 15 rejected more are searching longer, and it's -- and
 16 they also have higher reservation rates, because they
 17 know they're going to be rejected with higher
 18 probability, which makes them, in equilibrium, to
 19 settle with higher interest rates.
 20 So I guess maybe I should emphasize here, in
 21 the model, it is not always true that you are going to
 22 have, you know, search higher -- or you are going to
 23 get higher interest rate. It's an equilibrium
 24 prediction that seems to be born in the range of
 25 parameter values that we have.

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1 And the approval process leads to some sort of
 2 endogenous adverse selection at the lender level, and,
 3 you know, taking that into account is important
 4 because, you know, we don't want to, you know, infer
 5 from the fact that somebody's accepting a higher rate,
 6 that this person has higher search cost. It could be
 7 that this person could be, you know, higher risk
 8 credit type as well.
 9 So let me say a bit more about the data.
 10 Again, you know, this is some proprietary data that we
 11 got through a very resourceful set of co-authors. On
 12 conventional loans, it's a detailed, multilevel loan
 13 panel. Again, we have these two separate data sets.
 14 One is a sample of granted mortgages for which we have
 15 very detailed information about, you know, the
 16 characteristics and the ex post performance of the
 17 loan, so we see delinquency status.
 18 So along with the granted mortgages and their
 19 performance, we also have data on the applications and
 20 approval status of these loans. Then what we did is
 21 we matched these mortgage applicants and the grantees
 22 to their credit reports, using data provided by credit
 23 bureau, and these credit reports or the credit bureau
 24 data have information about the number of inquiries --
 25 the type of inquiries -- credit inquiries that are

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1 being made onto these people's records.
 2 And this data set, of course, doesn't have --
 3 has more than just the mortgage loan information. It
 4 has all things, like auto loans, student loans,
 5 consumer loans, et cetera. There's a lot of things.
 6 So pretty much everybody who has applied for a
 7 mortgage here knows the process. You know, there's an
 8 application, there's a credit review, and then there's
 9 a deposit, and it goes into underwriting at the bank,
 10 and then, finally, after 30 or 45 days or, you know,
 11 if your seller is somewhat sane, you know, in a
 12 relatively short amount of time, you close on the
 13 house.
 14 How about the -- the credit review, this is
 15 where, you know, a credit pull is done on your report,
 16 right? So the bank says to the -- one of the credit
 17 bureaus, we are going to do a credit pull, and this is
 18 going to be registered as an inquiry.
 19 Now, in this paper, we use a window -- in most
 20 specifications we used 45 days, but sometimes, you
 21 know, it can be 30 days, all of those inquiries as a
 22 proxy for search by the borrower. So you might ask,
 23 you know, are all these inquiries mortgage-related?
 24 You know, it is possible that, you know, some of these
 25 inquiries are done for credit cards or, you know,

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1 other types of loans, but actually if you look at the
 2 loans that appear in people's credit accounts, this
 3 period of about 30 to 45 days before a mortgage is
 4 approved is typically very silent, and -- you know,
 5 because a lot of people and, you know, their real
 6 estate agent or their broker or their friends will
 7 tell them, you know, sort of -- you know, you sort of
 8 don't want to -- you know, focus more on mortgages
 9 here, especially leading up to buying a house, you
 10 know, don't do too much searching around. After you
 11 get approved, you are going to get a lot more search
 12 behavior and other -- for other types of loans in the
 13 record, okay?
 14 So once again, okay, once you control for a lot
 15 of these covariates -- and my co-authors always tell
 16 me, sort of just, you know, say that we have a lot
 17 more covariates that -- you know, they argue that some
 18 other people have studied the data have used, so --
 19 and we have quite a few covariates here, and we still
 20 have, you know, a lot of residual dispersion, and, you
 21 know, it stays on even if you control for things like
 22 lender fixed effects. So these are sort of very sort
 23 of fine-level cuts of the data. You still get -- you
 24 are going to get price dispersion.
 25 What about the search angle? This is where we

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1 have less other kinds of information. So for the
 2 approved sample, the median person seems to search
 3 about two lenders, and, you know, below the median,
 4 there is only one lender, but there is a tail of
 5 people who seem to, you know, search three, four,
 6 five, you know, lenders before getting approved. The
 7 applicant pull, this is where this very long tail
 8 appears, you know, some of these people are -- have
 9 huge numbers of credit inquiries on their reports,
 10 and, you know, maybe not surprisingly they don't seem
 11 to get approved. They don't show up in the approval
 12 data.
 13 And the search patterns do seem to certify the
 14 creditworthiness of these borrowers. You go from sort
 15 of people who are -- you know, have low FICO scores,
 16 searching quite a bit more, to people with high FICO
 17 scores in detectable ways.
 18 That said, beyond creditworthiness, other types
 19 of demographics tend to not come in as clearly. For
 20 example, you know, if you do the breakdown by
 21 education, you get much smaller differences in search
 22 behavior, and, you know, we ran a whole bunch of
 23 regressions, and, you know, the number of -- the signs
 24 in which -- beyond what the FICO score predicts, how
 25 these covariates enter into search behavior doesn't

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1 seem to be that interesting or very intuitive in many
 2 ways, okay?
 3 So beyond, again, this FICO score difference,
 4 it does seem like the evidence on the search and
 5 characteristics is a bit mixed and difficult to
 6 interpret, so -- but let me now try to put these
 7 things in a little bit of model framework, and I will
 8 show you the main empirical findings here.
 9 Once again, sort of, you know, the intuition of
 10 basic search models, we expect higher search, it tends
 11 to be correlated with, you know, cheaper mortgages,
 12 finding sort of lower rates, and you might expect some
 13 of these characteristics to be correlative with, you
 14 know, the sophistication or the search costs of these
 15 consumers.
 16 And just to formalize it -- and then I am going
 17 to put the equations up, because I am going to modify
 18 them for our preferred model -- in the basic model,
 19 the sequential search model, there's some search costs
 20 that can be heterogenous across consumers, and people
 21 get some utility from the mortgage and get disutility
 22 from payment, the R-sub-Js, and the lenders are
 23 posting rates, and they're competing on rates.
 24 And the consumers are going to follow some
 25 reservation rate strategy. If they find -- if they

261	<p>1 get an interest rate draw that's below their</p> <p>2 reservation rate, they're going to stop and get that</p> <p>3 mortgage, and that defines cutoffs in the search cost</p> <p>4 distribution, which in turn defines the market shares,</p> <p>5 you know, of the different lenders depending on the</p> <p>6 interest rates.</p> <p>7 So if you simulate data from a model like this,</p> <p>8 where simply costs are given some bell-shaped, you</p> <p>9 know, truncated normal like this, and you generate the</p> <p>10 relationship between interest rates and inquiries, you</p> <p>11 are going to get a downward sloping pattern where, you</p> <p>12 know, the rate that you get, it declines with the</p> <p>13 number of inquiries that you make, precisely because,</p> <p>14 you know, people who have a higher number of inquiries</p> <p>15 have the lower search costs and have basically, you</p> <p>16 know, lower thresholds. They will not, you know, stop</p> <p>17 until they get the lower interest rate.</p> <p>18 So that was -- the previous one was theory, but</p> <p>19 this is data without controlling for anything. So</p> <p>20 this is for the approved sample. So interest rates as</p> <p>21 a function of inquiry show this -- you know, there's a</p> <p>22 decline apparent in the very beginning, but the U sort</p> <p>23 of turns in the wrong way when they go to higher</p> <p>24 inquiry levels, okay?</p> <p>25 And this is not just because of -- you know,</p>	263	<p>1 higher interest rates, which actually is -- you know,</p> <p>2 since we're putting in the FICO score as well, it does</p> <p>3 seem like, you know, there is something being screened</p> <p>4 on beyond FICO.</p> <p>5 So, once again, we want to say credit products</p> <p>6 are different, and then let me just sort of show you</p> <p>7 the model, did a simple tweak to the basic sequential</p> <p>8 search model that's going to generate hopefully the</p> <p>9 patterns that we see in the data. We are going to</p> <p>10 introduce some difference in credit quality, and we</p> <p>11 are going to introduce the screening process that</p> <p>12 these lenders can reject applicants.</p> <p>13 So once again we have a continuum of search</p> <p>14 cost distribution, but we have a difference in</p> <p>15 creditworthiness by the applicants. They are, you</p> <p>16 know, different, and there are two types in this</p> <p>17 market. You know, Gaston had a lot more types than we</p> <p>18 did in his paper. We are going to be much less</p> <p>19 ambitious and have only two types, a high type and a</p> <p>20 low type.</p> <p>21 And this is -- and all of our analysis is going</p> <p>22 to be conditioned on all these covariates, so this is</p> <p>23 the residual, if you will, unobservable heterogeneity</p> <p>24 that affects payment ability, you know, conditioned on</p> <p>25 all the observables.</p>
262	<p>1 so -- and this is actually -- you can see sort of how</p> <p>2 this could be generated due to the conflation of, if</p> <p>3 you will, different credit types and the search costs,</p> <p>4 because if you look at the people who have low FICO</p> <p>5 scores, the relationship is increasing, right? The</p> <p>6 number of inquiries, higher inquiries corresponds to</p> <p>7 higher interest rates.</p> <p>8 But even for people with relatively good</p> <p>9 credit, FICO scores above 720 -- and I don't know the</p> <p>10 population of distribution of FICO scores in this</p> <p>11 audience, it's probably pretty high, you know, I'm</p> <p>12 guessing a median of 800 or more or something, so it's</p> <p>13 going to -- it still shows the U-shaped pattern. It</p> <p>14 doesn't go along with theory, especially at the upper</p> <p>15 tail of the inquiry distribution.</p> <p>16 If we look at income, even for people who are</p> <p>17 relatively wealthy or have higher income, assume we</p> <p>18 have the same patterns, and, you know, across</p> <p>19 demographic groups, et cetera, this seems to go</p> <p>20 through, and let me just, you know, again residualize</p> <p>21 things, not to -- but if you put in a whole bunch of</p> <p>22 borrower controls, you still get this pattern, you</p> <p>23 know, once you control for a lot of things, including</p> <p>24 the FICO score, you get this pattern.</p> <p>25 People who search more, you know, are getting</p>	264	<p>1 And the utility for mortgage, we make it, of</p> <p>2 course, a function of your payment ability, and we can</p> <p>3 allow for adverse or advantageous selection based on</p> <p>4 the sign of the Sigma, as in many models. So if the</p> <p>5 low types have higher utility from the mortgage, you</p> <p>6 might expect some sort of adverse selection, but in</p> <p>7 terms of -- in this model, it's interesting, and I</p> <p>8 don't know how generic this prediction is in other</p> <p>9 models, that the sign of the Sigma just doesn't</p> <p>10 matter, you know, in the search model, because</p> <p>11 everything's based on the differential gains from the</p> <p>12 next search, the Sigma component just washes away, and</p> <p>13 what we're left with is a modified reservation rate</p> <p>14 equation, which is the middle equation here, where,</p> <p>15 you know, it used to be that I'm equating the search</p> <p>16 from -- the next search to the expected benefit of the</p> <p>17 search, and now I just scale the expected benefit of</p> <p>18 the search with your probability of being approved for</p> <p>19 the loan. That's the only difference in the model,</p> <p>20 okay?</p> <p>21 But this is what's going to happen if this Pk,</p> <p>22 which is your approval probability, is low, then</p> <p>23 that's going to increase your reservation rate, if you</p> <p>24 will, the R-upper-bar that you are going to try to</p> <p>25 search for, and so you are going to be willing to</p>

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1 accept higher prices, and, you know, in the same
2 amount of time, you are going to search less, and you
3 are going to be -- but because you're approved with
4 lower probability, you may have to search longer. So
5 you have this tension between you having, you know,
6 let's say a worse threshold, higher interest rate
7 threshold, but having to search longer because you are
8 not going to be approved easily.

9 How the supply side is going to be in this
10 model, and, you know, we have the supply side because
11 we would like to make some counterfactual simulations,
12 and, you know, see what -- how the equilibrium changes
13 in the market, and this turned out to be pretty
14 difficult problem actually.

15 And, you know, I should talk to David and his
16 co-authors, you know, they are masters in computing
17 these models, you know, carefully, and I love their
18 work because of that. It turns out sort of, you
19 know -- and I'll be super honest about this, I had
20 never written a paper with adverse selection in it
21 this way, and, you know, as the warnings from your
22 first year micro classes might say, the warnings from
23 the first year micro classes were true. These are
24 difficult models.

25 So it turns out, again, equilibrium existence

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1 is not always very easy, you know, markets unravel,
2 you know, there's no -- so what we did, you know, is,
3 you know, this is in some ways a dirty trick, is we
4 put a noise term in the profit function, the size,
5 basically for -- and we discretized the rates that
6 banks can post, which is the empirical reality in this
7 market.

8 They all seem to be, you know, clustered around
9 one-eighth of a percentage point, you know, offers,
10 and I have no idea why that is. It's a bit like the
11 SEC's stock ticker type stuff, and there might be some
12 interesting, you know, anticompetitive things to study
13 there. But assuming this discrete strategy space, you
14 put this noise in there, it turns into a Bayesian type
15 game where everything's a probability. You know, you
16 can search for a fixed point as if it's a mixed
17 strategy game, and that's how we sort of tried to
18 solve this problem on the supply side.

19 But I don't want to say, you know, that, you
20 know, that's the end of it, sort of -- it's a tough
21 problem to solve for, you know, supply side when
22 there's adverse selection that goes on in these
23 markets, and it's a very interesting set of economics
24 that goes into it.

25 So what about the lender? The lender's payoff

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1 is dependent, of course, on the rate that they get but
2 also the repayment probability, and the lender makes a
3 forecast of the repayment probability. So basically
4 they have this screening technology, basically this
5 probability is that they get the signal, and the
6 signal is whether there's a high type or a low type,
7 and depending on the signal, they approve or don't
8 approve the loan, okay?

9 So we simulated some of the data from this
10 model with some assumptions. For example, if you
11 assume that the -- Lambda is the proportion of high
12 types in the population, and about 70 percent good
13 types and 30 percent nonrepayment types, and the --
14 and we assume that the lenders have very good
15 discrimination ability, so they get basically the high
16 types, 95 percent probable to write, only 5 percent
17 they make a mistake.

18 So in that model, with search costs being the
19 same across the high types and the low types, what
20 you're going to get is the high-type consumers. The
21 only difference is they're -- you know, the type of
22 being creditworthiness are going to have much lower
23 reservation interest rates, and the low types are
24 going to have higher reservation interest rates, and
25 this is going to yield this upper sloping pattern that

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1 I showed in the data that, you know, in equilibrium,
2 in equilibrium rates that are being sent by the
3 lenders, that the lower types, if you will, search
4 longer even though they're willing to settle for a
5 higher interest rate. So the people who are sort of
6 doing a lot more inquiries are getting worse rates or
7 higher rates in this market.

8 And, again, you know, this is the distribution
9 of types across the different interest rates that are
10 being posted -- given by the lenders. As you increase
11 the interest rate, essentially after a point, after
12 about 2.5 percent, pretty much all of the people you
13 are getting are the low types. So this is really sort
14 of the adverse selection problem, you know, hitting
15 these lenders, okay?

16 So this simple model generates this dispersion
17 in prices, this positive empirical relationship
18 between search intensity and the prices of the rates,
19 and, again, the only sort of, you know, new ingredient
20 that we put in is this difference in creditworthiness
21 and some sort of, you know, somewhat effective
22 screening technology.

23 And, you know, we can have other predictions
24 from this model with creditworthiness and screening.
25 For example, we can ask, you know, how do defaults

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1 correlate with search intensity and are approvals
2 correlated with search intensity? So in the model,
3 for example, you know, we can generate an upward
4 sloping relationship between inquiries and default
5 rates.

6 You know, as we might intuit, people who do
7 more search are the lower types, so they default at
8 higher rates, and this is the data that, you know,
9 people who do more inquiries default much more often,
10 you know, even if you control for all these
11 covariates.

12 How about approval? You know, in our people
13 who are doing more inquiries, are they approved less
14 often? Well, in some ways, they have to. That's what
15 the model says, and that is what the data says, that
16 people who do -- you know, as I said earlier, the
17 people doing a lot of inquiries are approved a lot --
18 less frequently in the data.

19 So we might say, you know, so once -- you might
20 also say that, you know, why do you need search in
21 this model? Maybe it's this screening is just what's
22 creating this price dispersion, because, you know,
23 okay, maybe I convince you that there is some extra
24 sort of unobservables in this process that the lenders
25 are able to extract from looking at these applications

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1 and price accordingly. So maybe all of the price
2 dispersion is generated by that.

3 So to rule that out, what we looked at is the
4 set of what we call never-rejected borrowers. So
5 basically these are people who are very high -- credit
6 scores are very good credits -- credit risk. So these
7 are people, you know, whose FICO scores are basically
8 like people in this audience, above 800, low
9 loan-to-value ratios, that the income ratio is low,
10 you know, very vanilla contract, a 30-year, fixed-rate
11 mortgage.

12 And for these people, the mean approval rate is
13 about 99 percent, and the -- you know, the
14 relationship between inquiries and approval -- the
15 rates that you get is upward sloping as the standard
16 model predicts, and the -- sorry, this should be the
17 other one. The number of -- it should be downward
18 sloping as we predict, so this is the -- I'm trying to
19 think what's the left one, but -- so this is all
20 borrowers, so that's all par borrowers is upward
21 sloping.

22 For the never-rejected sample, it's downward
23 sloping, that the people who sort of are searching
24 more are getting lower interest rates in this
25 never-rejected or very good credit sample. And, you

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1 know, you can do it other ways. You can do it by
2 logit score, you know, look at the default rate
3 predicted and, you know, give the logit score to these
4 people and find the people who are above 97.5 logit
5 score, and for these people as well, then the interest
6 rate you get is, you know, at least on most parts of
7 the curve declining, maybe weakly declining in the
8 number of inquiries.

9 So what we would like to say from this is that
10 search does matter for these people, and, indeed, even
11 for this sample, there is quite a bit of search going
12 on. There's a lot of dispersion in the amount of
13 search that people are conducting. Some people tend
14 to do a lot more inquiries than others, and they get,
15 you know, better rates. So what I learned from this
16 is I should, you know, ask more banks for quotes, and
17 maybe I'll get a better rate down the line, but the --
18 yeah.

19 So to wrap this up, you know, we have this
20 model, again, that explains this nonmonotonic
21 relationship between, you know, search and rates, and
22 then, you know, I hope I was able to convince you that
23 search is somewhat important, but also the screening
24 and the importance of unobservable risk types or
25 adverse selections are also important in this market.

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1 So now that we have some facts to motivate the
2 model further, what we want to do is to sort of
3 estimate some model parameters maybe to get a handle
4 on how effective screening seems to be in this data,
5 you know, as it fits the moments that we observe in
6 the data, and maybe use this model to do some
7 counterfactuals.

8 So, once again, sort of, you know, one --
9 there's quite a few papers in the literature, and I'm
10 guilty of a few of them. You know, what we try to do
11 is we look at observed price dispersion and
12 distributions or both prices and quantities and try to
13 infer demand parameters, which in this case are search
14 costs, but the issue with this in this market is, you
15 know, what all those papers and techniques will give
16 you is the left-hand side of this equation, and the
17 right-hand side is what you see in the data,
18 dispersion of rates, et cetera. That's the theory of
19 the first order condition, if you will, of search
20 models, and the left-hand side is the search cost that
21 rationalizes what you see in the data.

22 But because we don't have the approval
23 probability in the denominator, we are going to get
24 the wrong inference on the search costs that we
25 observe in the data, if approval is an important part

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1 of this -- of these markets. So what we have in this
2 data, you know, because we have a setting with
3 unobserved types, unobserved credit types, how are we
4 going to get at that approval probability?

5 Well, we have approval data, but we also have
6 this mixture of people, you know, high types and low
7 types, you know, we can generalize it to have more
8 types, but we decide to stay with two types of
9 creditors -- of borrowers. So we have the search
10 information. We have the -- also the mortgage's
11 performance down the line, which allows us to get a
12 sense of what type of borrower this is, you know,
13 conditional on getting the mortgage, and to estimate
14 the parameters from the data.

15 And the parameters are somewhat interesting.
16 So they seem to indicate that, you know, screening is
17 informative, that, you know, the banks are able to get
18 the high type, you know, so -- so -- so I'm trying
19 to -- 80 plus 2X, and so X is 10 percent, so it's
20 about 90 percent probability of getting the high type
21 right, with 10 percent, you know, mistake in getting
22 the high types right. That's what the 79 percent
23 means.

24 And there seem to be quite a few bad risks in
25 this applicant pool. If you will, about 50 percent of

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1 them are actually sort of -- should not qualify for
2 this. They are, you know, people who are not going to
3 repay with high probability.

4 There is some default by high types, you know,
5 as the model classifies the borrowers. About 90
6 percent of them, you know, default in the data, but --
7 and so 10 percent of them default, but 70 percent of
8 the bad types will default in the data. That's what
9 the model yields.

10 What about the search costs? Well, the
11 search -- even if you account for this
12 creditworthiness heterogeneity, it is substantial, you
13 know, it's about 27 basis points. If you try to do it
14 by year or over the 30-year life of the loan, it's
15 about \$10,000. So you are basically paying \$10,000
16 more over the life of the loan because, you know,
17 you're not searching one more lender. And then there
18 is heterogeneity in search costs, and the percentiles
19 are somewhat different.

20 And these numbers are broadly consistent with
21 other findings in the literature about search in
22 markets where credit -- financial product markets
23 where approvals are not that important. J.F. can, you
24 know, say otherwise, but I think in their market, this
25 wasn't -- you know, those were sort of -- approvals

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1 were not that important a feature of their market, so
2 they find other -- they found similar order of
3 magnitude search costs, and in other financial product
4 markets I know of, these are similar types of numbers.

5 And the model, even though it's very stylized,
6 does fit the -- you know, the basics of the data
7 relatively well, and so the -- we are still -- you
8 know, the reason this paper is not out the door is
9 because we haven't done as much as we would like in
10 counterfactuals, but I will show you what we have so
11 far.

12 So one thing we wanted to do, my colleagues
13 being more sort of finance macrotypes, they were
14 interested in how sort of monetary policy changes are
15 transmitted in the mortgage markets. I said I don't
16 know too much about that, but they wanted to look at
17 ten basis points in reduction of cost, how is it
18 transmitted in this market? Was it passed through?

19 Essentially the answer is, in this model, it's
20 about one-for-one pass-through, so it's a -- you know,
21 even though there's a lot of sort of, you know, search
22 costs, you know, all this adverse selection goes on,
23 pass-through still seems about one for one.

24 Another one that's maybe a bit more interesting
25 is a calculation that is counterfactual regarding

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1 redlining practices. So this is a very nice picture
2 that Gregor found in some court records about this
3 bank, Evans Bank in Buffalo. This is a court
4 document. They actually sort of, you know, redlined
5 the areas where they operate, and the hashed lines are
6 the places where the population is very -- majority or
7 near majority are African-American, where they do not
8 operate.

9 So -- and there was a lot of redlining lawsuits
10 of this kind, and what we tried to do in this
11 simulation is, you know, instead of doing explicit --
12 so instead of doing discrimination on rates, based on
13 race, we are going to do the discrimination on the
14 approval of these creditors. So basically some of
15 these banks are going to systematically approve the
16 applications of certain kinds of applicants with much
17 lower probability than others, and -- which means
18 basically that approval probability is going to be
19 sort of penalized by this discrimination factor.

20 So what's going to happen is that the
21 discriminated group in this model realizes this or
22 learns about this once they've done a few
23 applications, so that they are going to approve with
24 less -- with lower probability, so they are going to
25 search longer, but they are also going to raise their

277	<p>1 reservation interest rate. So they are going to 2 settle for a lower mortgage.</p> <p>3 So what this is going to -- what this is going 4 to do is even if there's no explicit discrimination on 5 the rate, because this group is essentially acting 6 like -- you know, more inelastic demand, the rates 7 that these banks are going to offer are going to rise, 8 and because in this model we assume that the consumers 9 do not know which bank is discriminating, and they are 10 going to approach each lender with the same higher 11 reservation interest rate, so what's going to happen 12 is that the nondiscriminating banks as well are going 13 to charge higher loan rates in equilibrium in this 14 model.</p> <p>15 So what's going to happen is that the overall 16 interest rates are going to go up quite a bit, the 17 average interest rate, and actually sort of the amount 18 of searches that, you know, that have to be done in 19 the market is going to rise as well. So the mean 20 origination rate is going to -- and it depends on the 21 percentage of people who are redlined against, of 22 course, and then these other parameters, but, you 23 know, I think -- and the interesting aspect is the 24 strategic complementarity, if you will, if the 25 discriminators, but the redliners are, you know,</p>	279	<p>1 screening. And you can try to do exercises where you 2 may see the shutoff screening, and, you know, we look 3 at the effects of this type of policy.</p> <p>4 An interesting sort of overall message that we 5 get from it is, you know, the changes in equilibrium 6 offered rates especially come from two sources. One 7 is the demand side adjustment, you know, people 8 changing their reservation interest rate, but also how 9 the supply side reacts by the offers that they give. 10 It appears that most of this, you know, when you shut 11 down the supply response, if you will, and you look at 12 only the effect of the demand side, you don't get as 13 much movement in these equilibrium quantities. The 14 supply adjustment component is much more important 15 quantitatively than the demand side effect on these 16 equilibrium outcomes, okay?</p> <p>17 So let me stop here. There's a zero there, and 18 so I just want to say again, you know, search has been 19 a very fruitful area, you know -- of course, since 20 1961, I saw about 9000 Google Scholar cites on 21 Stigler's paper, probably many more, on, you know, 22 explicit citations. You know, a lot of people think 23 about search models.</p> <p>24 What we want to do is here, you know, in these 25 credit markets or financial products markets,</p>
278	<p>1 cutting down on the approvals, and all loan rates go 2 up for a -- against this discriminated group. So 3 essentially the market discriminates against these 4 people through this effect.</p> <p>5 Other things we did, you know, what about 6 tighter lending standards? So we definitely see in 7 the data, when we do it by subsamples, that the shift 8 in these screening probabilities -- one anecdote to 9 motivate this is, you know, we read somewhere that Ben 10 Bernanke was rejected for a refinance loan, you know, 11 at the -- near the height of the crisis, so there was 12 a time where -- you know, after 2008 where banks got 13 very, very sort of conservative, if you will, in their 14 screening practices.</p> <p>15 It does sort of affect, you know, people's 16 search and acceptance probabilities, reservation rates 17 quite a bit, and it increases the interest rates by 18 about -- by some, and the model search introduced -- 19 that's done by these people, which is definitely the 20 people seem to be searching more during the crisis 21 times in our data.</p> <p>22 On the reverse side of it, there are policy 23 interventions, like the Community Reinvestment Act, 24 which is basically regulations that weaken strict 25 screening technologies. These are restrictions on</p>	280	<p>1 especially the screening or approval process has also 2 become an important aspect of it, and we need to take 3 this into account.</p> <p>4 Again, I would like to push this -- you know, I 5 am going to try to do it, but if people are 6 interested, I think the -- how these institutions do 7 screening is very important and how sort of the 8 regulations affect these screening technologies, how, 9 you know, these organizations use data to screen 10 people is also very important, you know, in 11 determining equilibrium outcomes.</p> <p>12 So, you know -- and then, again, sort of not 13 just credit markets, but lots of insurance markets, 14 you know, fall under this point of view, and sort of I 15 think, you know, over the last decade or so, there's 16 been a lot of work on markets with -- you know, 17 markets we call selection markets or markets with 18 adverse selection, bringing the theory and empirics 19 together, but, again, I want to say there can be 20 nontrivial implications of this in the data and also 21 in the -- you know, in the execution of these, and I 22 think it's going to be, you know, very interesting and 23 challenging times for, you know, applied economists 24 for some time to come.</p> <p>25 Thank you so much for inviting me.</p>

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1 (Applause.)
2 MR. ROSENBAUM: Thank you, Ali.
3 We have a reception outside, and we will
4 continue the conversation there. Thank you all very
5 much.
6 (Whereupon, at 5:20 p.m., the proceedings were
7 adjourned.)
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A				
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In the Matter of:

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1	3
1 UNITED STATES FEDERAL TRADE COMMISSION	1 P R O C E E D I N G S
2	2 - - - -
3	3 W E L C O M I N G R E M A R K S
4 THE ELEVENTH ANNUAL	4 MS. DUTTA: Hi, everyone, and welcome to the
5 FEDERAL TRADE COMMISSION MICROECONOMICS CONFERENCE	5 first session of the second and final day of the FTC
6	6 Microeconomics Conference. This session was organized
7	7 by Katja Seim of the University of Pennsylvania, who's
8	8 a member of the Scientific Committee for the
9 Federal Trade Commission	9 conference this year.
10 FTC Constitution Center	10 As you may have seen with the sessions
11 400-7th Street, S.W.	11 yesterday, there will be two papers presented during
12 Washington, D.C.	12 the session. For each paper, the presenter will have
13	13 25 minutes to present the paper, which will then be
14 Friday, November 2, 2018	14 followed by the paper discussant, who will have 10
15 9:00 a.m.	15 minutes, and then finally we will have about 10
16	16 minutes for Q&A.
17	17 (End of Welcoming Remarks.)
18 Sponsored by:	18
19 Federal Trade Commission Bureau of Economics	19
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1 C O N T E N T S	1 P A P E R S E S S I O N :
2	2 H O W A C Q U I S I T I O N S A F F E C T F I R M B E H A V I O R A N D P E R F O R M A N C E :
3 SESSION: PAGE:	3 E V I D E N C E F R O M T H E D I A L Y S I S I N D U S T R Y
4 WELCOMING REMARKS	4 MS. DUTTA: So I would like to invite Ryan
5 MS. DUTTA 3	5 McDevitt of Duke University to present the first paper
6 PAPER SESSION:	6 of this morning, which considers the effect of
7 HOW ACQUISITIONS AFFECT FIRM BEHAVIOR AND	7 acquisitions on firm behavior and performance in the
8 PERFORMANCE: EVIDENCE FROM THE DIALYSIS	8 dialysis industry.
9 INDUSTRY 4	9 Ryan, welcome.
10 MR. McDEVITT 4	10 MR. McDEVITT: Well, thank you very much for
11 MR. WILSON 24	11 letting me be on the program. It's very exciting to
12 PAPER SESSION:	12 be here. It's a great conference, great audience,
13 NONPARAMETRIC ESTIMATES OF DEMAND	13 although this reminds me of an MBA classroom at 9:00
14 IN THE CALIFORNIA HEALTH INSURANCE	14 a.m. There will be some stragglers coming in, I
15 EXCHANGE 41	15 suppose.
16 MR. TEBALDI 41	16 This is joint work with Paul Eliason. He just
17 MS. HO 58	17 started at BYU as an assistant professor. He's doing
18 KEYNOTE ADDRESS, "OWNERSHIP CONCENTRATION	18 great work, a lot of it in the dialysis industry; and
19 AND STRATEGIC SUPPLY REDUCTION" 76	19 Ben Heebsh, he's a current Ph.D. student, and he will
20 MS. SEIM 77	20 be on the market next year, I believe somewhere in
21 PANEL: ESTIMATING MARKUPS 104	21 health economics. He will be a great person to look
22 MR. RAVAL 104	22 at. And then Jimmy Roberts is also on this paper.
23	23 The main motivation for our paper today is
24	24 we're going to look at the consolidation in the
25	25 healthcare industry. As we all know, there has been

5	<p>1 rampant consolidation over the past few decades, and 2 as IO economists, we're in a great position to analyze 3 the effects of this consolidation. 4 The current state of literature in IO mostly 5 focuses on the effect of concentration on outcomes 6 like prices and quality. Typically more concentrated 7 markets have higher prices and lower quality, but the 8 literature that we're aware of, it mostly looks -- its 9 concentration is somewhat of a black box and how that 10 affects the outcome. There's some measure of HHI on 11 the right-hand side, and then these outcomes are on 12 the left-hand side. 13 Our talk today will focus more on what's going 14 on behind the scenes. How does the firm actually move 15 from an acquisition to effecting outcomes? We want to 16 dig in, in a very precise way, and understand how 17 these prices and how this quality changes after a 18 merger/acquisition. 19 And we came upon this topic based on two of our 20 previous papers. In long-term care hospitals, I 21 worked on this setting with some of the co-authors on 22 this paper, and long-term care hospitals specialize in 23 patients who have very prolonged needs. They have 24 been in a car accident and they need assistive 25 breathing; they are in the hospital for several</p>	7
6	<p>1 months. And Medicare has a quirky reimbursement 2 system where they give a short per-day reimbursement 3 for the first few days of the stay and then a lump sum 4 that's supposed to cover the whole length of the stay 5 after about two or three weeks. 6 Based on this compensation scheme, long-term 7 hospitals tend to discharge patients right after they 8 reach that lump sum threshold, which obviously 9 distorts care that's not efficient from the patient's 10 perspective, but we were very intrigued by the result 11 that after the long-term care hospital chains, there 12 are two big chains in this industry. Once they 13 acquire independent hospitals, they tend to implement 14 this strategy more often. It seems like there's some 15 kind of transference of best practices from a profit- 16 focused standpoint. 17 We then can combine that with a paper I worked 18 on with Paul Grieco, where we look at what we call the 19 quality/quantity tradeoff in dialysis, where some 20 for-profit chains tend to emphasize quantity over 21 quality, because it's more profitable to do so, and so 22 synthesizing these two results will be the main focus 23 of our paper today. 24 To do our analysis, we're going to look at 1200 25 acquisitions that have taken place over the past 15</p>	8
6	<p>1 years in the U.S. dialysis industry, and this is a 2 great setting for our purposes because the large 3 chains here, DaVita/Fresenius, they behave very 4 differently than the independent facilities. 5 They use more injectable drugs, for instance, 6 because they're very profitable during the time period 7 of our study; they replace nurses with techs because 8 nurses are more expensive than techs; they treat more 9 patients per employee and station, trying to be more 10 efficient, stretch their resources. 11 And in doing this it leads to worse outcomes 12 for patients. We find that survival and transplant 13 rates fall once an independent facility is acquired, 14 and hospitalizations increase. This, of course, 15 wastes Medicare's scarce resources. Medicare is 16 paying more for lower quality outcomes. 17 There has been much work on this topic, both 18 within healthcare and outside, by IO economists. I 19 can't spend any time on this really, I have only 25 20 minutes, and this is not an exhaustive list by any 21 stretch, but we think of three main buckets of 22 literature right now on this topic. 23 The first is that looking within healthcare and 24 even in other industries, typically you don't consider 25 mechanisms, but how quality and prices change. Again,</p>	7
6	<p>1 they look at a very reduced-form way of how 2 concentration then affects the outcomes. So we're 3 going to build on that by looking precisely at the 4 mechanisms. 5 There has been some work on how firms transfer 6 their strategies after an acquisition, and there's 7 going to be evidence here that managers implement 8 these best practices within dialysis. And, of course, 9 within healthcare, the reimbursement scheme for 10 Medicare matters a lot for providers' behavior, and 11 we're going to show, just like we did with long-term 12 care hospitals, that these providers respond to 13 incentives. Not a mind-blowing result, but we can 14 show precisely how this happens. 15 I'll give you a few brief details about 16 dialysis. It's an important industry within 17 healthcare, covers a lot of patients. A patient who 18 needs dialysis because they have kidney failure -- and 19 the kidneys perform two main functions within the 20 body. They filter toxins from the bloodstream and 21 they also stimulate the production of red blood cells. 22 If you have kidney failure, the kidneys no longer 23 perform those functions, so you need a replacement to 24 continue to live. 25 The two options for this are dialysis, where</p>	8

9	<p>1 you see in the pictures you go into a facility, you're</p> <p>2 hooked up to a machine, and that machine replaces the</p> <p>3 function of the kidneys, it filters blood and toxins,</p> <p>4 or you can receive a transplant. That's the most</p> <p>5 preferred option. That's the only way to actually</p> <p>6 cure this condition.</p> <p>7 The issue, though, is that kidneys are scarce,</p> <p>8 there aren't enough to go around, and so practically</p> <p>9 speaking, all patients with kidney failure at some</p> <p>10 point go on dialysis.</p> <p>11 In the United States, dialysis is an outsized</p> <p>12 influence on spending on healthcare. There are about</p> <p>13 500,000 patients across the United States, and 90</p> <p>14 percent of these are covered by Medicare. In the</p> <p>15 seventies, Congress enacted legislation that covered</p> <p>16 kidney care in the United States for all patients</p> <p>17 regardless of age. In John Oliver's segment on the</p> <p>18 dialysis industry, he made the joke that it's like one</p> <p>19 organ of the body in the U.S. is Canadian, the</p> <p>20 kidneys, because we have universal coverage.</p> <p>21 There's an 80/20 split with Medicare Part B, so</p> <p>22 patients pick up 20 percent of the costs, and if they</p> <p>23 have private insurance, that covers the first 30</p> <p>24 months. And this will be an important feature of this</p> <p>25 industry, because privately insured reimbursements are</p>	11
10	<p>1 much larger than Medicare reimbursements.</p> <p>2 But the bottom line is, we spent over \$30</p> <p>3 billion a year on this, at 6 percent of Medicare's</p> <p>4 budget and actually 1 percent of the overall federal</p> <p>5 budget. This is a huge issue and it's growing</p> <p>6 considerably over time.</p> <p>7 Now, I'll briefly go through Medicare's payment</p> <p>8 structure for dialysis. During the time period of our</p> <p>9 study, centers paid a composite rate of -- were paid a</p> <p>10 composite rate of \$128 per treatment, up to three</p> <p>11 times per week, but drugs like EPO and some other</p> <p>12 injectable drugs were paid on a fee-for-service basis.</p> <p>13 Of course, this led to some wasted resources.</p> <p>14 Centers put too much EPO into patients, so Medicare</p> <p>15 reformed payment in 2011, and now it's \$230 for</p> <p>16 treatment and drugs within one bundle. And you can</p> <p>17 see from this figure that after the bundle reform in</p> <p>18 2011, use of injectable drugs fell considerably, which</p> <p>19 to us suggests that the behavior of centers is really</p> <p>20 influenced by this payment structure.</p> <p>21 EPO is going to be a main focus of our paper.</p> <p>22 It treats anemia. It's used by 90 percent of dialysis</p> <p>23 patients at any given time, and it was the largest</p> <p>24 drug expenditure for Medicare for many, many years,</p> <p>25 almost \$2 million in spending in the late 2000s.</p>	12
9	<p>1 Facilities would get \$10 per 1000 units in</p> <p>2 reimbursement, and this added up to 25 percent of</p> <p>3 DaVita, one of the largest chains in dialysis, of</p> <p>4 their revenue, and 40 percent of their profits. So</p> <p>5 this is a huge profit center during the time period of</p> <p>6 our study.</p> <p>7 The structure of this industry, there are about</p> <p>8 7000 facilities across the United States, and growing</p> <p>9 more each year, and two large chains that dominate</p> <p>10 this. So think of this as a duopoly, DaVita/ Fresenius, two for-profit chains, and despite their</p> <p>11 claims in the press that they aren't reimbursed enough</p> <p>12 to actually cover their costs, they're very</p> <p>13 profitable, and those profits have been going up over</p> <p>14 time.</p> <p>15</p> <p>16 And to give you a sense of how this industry</p> <p>17 has evolved over the past decade or so, we can see the</p> <p>18 growth in facilities but also that DaVita and</p> <p>19 Fresenius are becoming more concentrated. They own</p> <p>20 now up to two-thirds of all facilities, and a lot of</p> <p>21 that has come through acquisition.</p> <p>22 And here's the plot of acquisitions over time</p> <p>23 and how they've grown. The bottom dark blue segment</p> <p>24 of this figure is independent acquisitions. That's</p> <p>25 what we're going to focus on in our work. The big</p>	11

13	<p>1 company events to really make that point.</p> <p>2 And so I'm just trying to demonstrate in this</p> <p>3 slide that strategy is very important, culture is very</p> <p>4 important for these facilities, so that's a channel</p> <p>5 through which facilities might change their behavior</p> <p>6 after acquisition.</p> <p>7 So our measures for the effects of</p> <p>8 acquisitions, we're first going to look at observable</p> <p>9 provider choices, aspects like injectable drugs, EPO,</p> <p>10 for instance; we'll get staffing decisions, whether</p> <p>11 they have nurses or techs; we'll look at the overall</p> <p>12 staffing level, how many resources they put into the</p> <p>13 facilities. We'll then see how these influence</p> <p>14 clinical measures like what we call the urea reduction</p> <p>15 ratio, how much of their toxins are cleaned through</p> <p>16 dialysis; and also hemoglobin, what's your blood level</p> <p>17 like after you get injections of EPO.</p> <p>18 And then we'll also look at patient outcomes,</p> <p>19 factors like hospitalizations, mortality transplants,</p> <p>20 and that will allow us to also measure some aspect of</p> <p>21 quality.</p> <p>22 And the reason we can do any of this with our</p> <p>23 paper is that we have really incredible data for the</p> <p>24 dialysis industry. Because Medicare is the primary</p> <p>25 payer for all dialysis patients, they make all the</p>	15	<p>1 And so really, instead of a summary table, we're going</p> <p>2 to show you the regressions, and those will be much</p> <p>3 more telling of what's going on.</p> <p>4 Identification strategy is very</p> <p>5 straightforward. Think of the simple dif-in-dif,</p> <p>6 where we're going to look at how an acquisition</p> <p>7 affects outcomes, and the two primary threats to</p> <p>8 identification here will be first it could be that</p> <p>9 patient mix changes after acquisition, and so it's not</p> <p>10 the acquisition itself that changes outcomes, it's</p> <p>11 just you're looking at different types of patients,</p> <p>12 and for that we're going to rely on very robust</p> <p>13 clinical and patient data to understand how these</p> <p>14 effects are changing.</p> <p>15 And the other key issue is that obviously</p> <p>16 acquisition is not random. These chains are picking</p> <p>17 off facilities, and to control for that, we're going</p> <p>18 to include facility fixed effects, which will be</p> <p>19 crucial, because we're looking at, within a facility,</p> <p>20 how behavior changes after acquisition. That means</p> <p>21 identification is truly from within physical changes</p> <p>22 in ownership, and we'll also show you there's no trend</p> <p>23 prior to acquisition. So we're okay in a dif-in-dif</p> <p>24 sense.</p> <p>25 And our advantages here in this setting over</p>
14	<p>1 data available to researchers, so we have over 14</p> <p>2 million patient months at a very detailed level.</p> <p>3 Every month a facility must file claims, and we have</p> <p>4 the claims data -- nonitemized, of course -- but we</p> <p>5 see for each patient, for instance, how much drugs</p> <p>6 they receive, what kind of treatment they receive,</p> <p>7 their blood measures, their infection rate, their</p> <p>8 hospitalization rate. Everything that we would want</p> <p>9 to measure, we have access to that in the data.</p> <p>10 To give you a sense of what's in our data, here</p> <p>11 are just some selected summary statistics broken down</p> <p>12 into four categories. We think of facilities as being</p> <p>13 always independent, and then the independent acquired</p> <p>14 facilities, we look at them before and after</p> <p>15 acquisition, and then we also have facilities that are</p> <p>16 always a part of a chain. And you can see from this</p> <p>17 table, there are really noticeable differences, at</p> <p>18 least in an observable way, across these four</p> <p>19 categories.</p> <p>20 And some that pop out are really due to the</p> <p>21 time series, just of evolution and trends over the</p> <p>22 time period. For instance, ischemic heart disease has</p> <p>23 fallen considerably across the U.S., and clearly</p> <p>24 because we have a post-acquisition dummy, that sample</p> <p>25 is from later periods when heart disease has fallen.</p>	16	<p>1 previous studies, first we have a very large sample of</p> <p>2 acquisitions. 1200 is the largest we've seen. Of</p> <p>3 course, we would be happy to see other papers that</p> <p>4 also work on this, if we haven't covered them yet, but</p> <p>5 1200 is a very large number for acquisitions.</p> <p>6 We also have cleared channels through which</p> <p>7 strategies could change after acquisition. There's a</p> <p>8 limited scope or change in prices here because</p> <p>9 Medicare unilaterally dictates reimbursements.</p> <p>10 There's not much going on in terms of price</p> <p>11 competition. And there's little evidence here that</p> <p>12 market power matters, at least for Medicare patients.</p> <p>13 We'll show you some results at the very end, and</p> <p>14 that's more the work of Paul Eliason, but it really is</p> <p>15 to worry about firm strategy, not about competition.</p> <p>16 And here is the main figure for the paper. If</p> <p>17 you gave me only one slide to present today, this is</p> <p>18 the slide I would show. In this figure, we have EPO</p> <p>19 dosing at acquired firms, in the left-hand side of the</p> <p>20 panel is months prior to acquisition, right-hand side</p> <p>21 is months after acquisition. And you can see clearly</p> <p>22 there's no trend before acquisition, very flat, this</p> <p>23 is normalized coefficients. It's very flat EPO</p> <p>24 dosing.</p> <p>25 And then after acquisition, a very sharp</p>

17	<p>1 increase in EPO doses, which can't be explained by 2 clinical necessity. It's purely the result of firms 3 seeking profits. For us this was a very stark finding 4 and really what we're going to build the rest of the 5 analysis around. 6 That figure comes from a regression, and this 7 regression, we can think of it in a few different 8 ways, but I think the most restrictive, most 9 conservative regression is in column 4, where we have 10 a host of controls plus key fixed effects, including 11 year/month fixed effect, patient facility controls, 12 facility fixed effect, in addition to patient fixed 13 effects. 14 So that means identification is coming from 15 within a patient, after a facility is acquired, how 16 does that patient, himself or herself, change in terms 17 of EPO? And so that's a very conservative regression 18 and we're very confident in these results. 19 Another injectable drug to look at, Venofer and 20 Ferrlecit, these are iron supplements. People on 21 dialysis are often deficient in terms of iron, so they 22 receive an injectable drug. And here you see a clear 23 pattern where, after acquisition, the use of Ferrlecit 24 drops and the use of Venofer increases. And the 25 explanation here is that Venofer is reimbursed at a</p>	19	<p>1 And because these patients are hooked up, their 2 blood is exposed to a machine, that means they're 3 susceptible to infections. If we don't clean it 4 thoroughly, that means a higher turnover makes it a 5 greater risk for infection, and this is borne out in 6 the data. We find that patients at acquired 7 facilities mostly fare worse after acquisition. 8 For instance, all cause hospitalizations go up 9 6 percent, and again, this is very (indiscernible). 10 Looking at this very same patient, before and after 11 acquisition, what happens. Their risk of going into 12 the hospital goes up 6 percent. Risk of a blood 13 infection goes up almost 3 percent. This is one of 14 the most severe conditions you can have, very hard to 15 recover from, very painful, very costly to Medicare in 16 terms of hospitalizations, and, again, the story here 17 is that because they have more patients on each 18 station and fewer nurses and techs to clean the 19 machines, they're at greater risk of acquiring a blood 20 infection. 21 Also, EPO doses at too large a dose increases 22 patients' risk for a cardiac event, and we see those 23 go up almost 4 percent. And, again, this is a very 24 bad outcome for patients. They're at risk for this, 25 and we see because they're getting doses of EPO that</p>
18	<p>1 higher rate, even though they're perfect substitutes, 2 just some quirk in the packaging and the size of the 3 vials they use. And so, again, it's a clear profit 4 motive. If you use more Venofer, your profits will go 5 up, even though from the patient standpoint, they're 6 equivalent. 7 In terms of resources, we look at certain 8 ratios, for instance, nurses over techs. Nurses are 9 higher skilled, but they're more highly paid; they 10 have higher wages. And we see that the nurse to tech 11 ratio is about one to one before acquisition, right? 12 After acquisition, it falls 15 percent. So it appears 13 as though the for-profit chains' nurses -- they 14 substituted techs for nurses because it cuts their 15 costs, and potentially that will have an effect on 16 outcomes that I will show you in a moment. 17 They also stretch the employees by putting more 18 patients per employee. The patient-per-employee ratio 19 increases by 12 percent. And they also have more 20 patients per station. Patients per station goes up 21 4 1/2 percent, and it's going to be very bad for 22 dialysis, because patients per station, for instance, 23 means that they have more turnover on each station, 24 which means they have less time to clean the machines 25 between use.</p>	20	<p>1 are too high, their risk of a heart attack goes up. 2 We can also look at less acute measures from 3 clinical outcomes from the dialysis itself. Good URI 4 is probably the one measure we find where there's 5 unambiguous increases in quality after acquisition. 6 Patients with good URI, meaning their blood has been 7 cleaned of more toxins, that goes up 2 1/2 percent 8 after acquisition. 9 Low hemoglobin falls because of all the EPO, 10 that's a very small change, even though statistically 11 significant. But on the other side of that, high 12 hemoglobin goes up by 4 percent, which is bad in the 13 sense that it increases the risk of cardiac events. 14 And good hemoglobin within the recommended range, that 15 falls by 3 percent. 16 And probably the most important statistics for 17 patients is how likely they are to survive dialysis or 18 get a transplant, and based on our analysis and both 19 measures, patients do worse after acquisition; less 20 likely to be on the wait list to receive a transplant 21 within the first year, that falls 9.4 percent. 22 And again, a transplant is the only way to cure 23 this condition. It's the most preferred outcome, most 24 preferred treatment option for kidney failure, but a 25 tradeoff for a facility is if someone gets a</p>

21	<p>1 transplant, then they're no longer a customer for the</p> <p>2 dialysis facility, so they have a conflict of interest</p> <p>3 there.</p> <p>4 And there are some lawsuits that look at just</p> <p>5 that issue, where DaVita/Fresenius have been accused</p> <p>6 of not promoting transplants or being on the wait list</p> <p>7 for their patients, which conflicts with federal</p> <p>8 guidelines.</p> <p>9 Patients are also 1.7 percent less likely to</p> <p>10 survive their first year of dialysis. Mortality rates</p> <p>11 are higher after acquisition. Again, a very bad</p> <p>12 result for patients, I think it should go without</p> <p>13 saying.</p> <p>14 And then the bottom line number for Medicare,</p> <p>15 payments go up about 7 1/2 percent after acquisition,</p> <p>16 and this is what the facilities are trying to</p> <p>17 implement with their strategies. They're profit-</p> <p>18 maximizing entities. They want reimbursements to go</p> <p>19 up, and they've achieved this mostly through drug use,</p> <p>20 but on the cost side as well, we see the costs decline</p> <p>21 after acquisition. So revenue up, costs down, profits</p> <p>22 are going up considerably at these facilities.</p> <p>23 So to conclude briefly on -- I can spend some</p> <p>24 time on this slide, but the bottom line from our study</p> <p>25 is that acquisitions lead to worse outcomes for</p>	23	<p>1 understand why competition doesn't matter in this</p> <p>2 industry. Our hypothesis is it's because of these</p> <p>3 travel costs, but it's something we want to spend more</p> <p>4 time on as we revise the paper.</p> <p>5 We also have a number of future projects we</p> <p>6 want to work on in this industry. The first is a</p> <p>7 study of EPO use after bundle reform in 2011. I</p> <p>8 showed you the figure where EPO use fell considerably</p> <p>9 right after payment reform, which, again, is not</p> <p>10 surprising, because reforming the bundle meant that</p> <p>11 EPO went from pure profit, they got a markup over the</p> <p>12 wholesale cost of the EPO drug, but after bundle</p> <p>13 reform, that became pure cost because it was part of</p> <p>14 the bundle. So pure marginal cost, which means as the</p> <p>15 firm is trying to maximize profits, they will use less</p> <p>16 EPO.</p> <p>17 We are going to look at that specifically in</p> <p>18 another paper, and here we have a great potential</p> <p>19 instrument. The elevation of the patient affects the</p> <p>20 size of their EPO dose. At higher elevations, your</p> <p>21 blood just naturally produces enough red blood cells,</p> <p>22 you naturally have enough red blood cells, and so we</p> <p>23 use that instrument to understand who will be more</p> <p>24 affected by a change in payments for EPO.</p> <p>25 The second paper we want to write on this</p>
22	<p>1 patients, higher reimbursements for Medicare, which</p> <p>2 means the overall value of these treatments have</p> <p>3 unambiguously fallen, where the payers are paying more</p> <p>4 for worse quality of care, a very poor result.</p> <p>5 And one aspect of our study that I didn't spend</p> <p>6 much time on today is that there's not much evidence</p> <p>7 that competition matters in dialysis. We think of</p> <p>8 these facilities as being their own individual local</p> <p>9 monopolies, and Paul Eliason has spoken on this</p> <p>10 extensively in his job market paper, because these</p> <p>11 patients are in very poor condition, often very low</p> <p>12 income. They have very high travel costs to get to a</p> <p>13 facility. So there's very little switching that goes</p> <p>14 on regardless of quality.</p> <p>15 So once the quality falls at the acquired</p> <p>16 facility, there's not much response from consumers,</p> <p>17 which is puzzling if you think of free choice here and</p> <p>18 you are free to choose any facility that's available,</p> <p>19 but they don't switch because travel costs are so</p> <p>20 important. They're almost always going to one that's</p> <p>21 closest to them. We see fewer than 1 percent of</p> <p>22 patients switch each year even when quality falls</p> <p>23 dramatically.</p> <p>24 So the next part of our study, we're going to</p> <p>25 really focus on this competitive aspect and try to</p>	24	<p>1 setting looks at what we call the make or buy decision</p> <p>2 for facilities. These chains have acquired a number</p> <p>3 of facilities that we see in this figure, but they</p> <p>4 also do a lot of new investment, and there is even a</p> <p>5 little bit of exit. And so we want to understand how</p> <p>6 access is affected by payment reforms.</p> <p>7 One counterpoint to all this is that maybe we</p> <p>8 wouldn't have any facilities at all if they weren't</p> <p>9 allowed to earn such profits from cutting quality; we</p> <p>10 don't see much evidence of that. And another argument</p> <p>11 against that is that the U.S. outcomes are much worse</p> <p>12 than in other industrialized nations, which shows it</p> <p>13 is possible to have this industry without such payment</p> <p>14 reforms, but we want to focus specifically on a more</p> <p>15 structural model to understand when facilities enter a</p> <p>16 market and how that's influenced by payments.</p> <p>17 Thank you very much, and I'm looking forward to</p> <p>18 the discussion.</p> <p>19 (Applause.)</p> <p>20 MS. DUTTA: All right. Thank you, Ryan. The</p> <p>21 discussant for this paper is the FTC's very own Nathan</p> <p>22 Wilson.</p> <p>23 Nathan?</p> <p>24 MR. WILSON: Well, thank you very much for your</p> <p>25 attention, and thanks, everyone, for coming out. I</p>

25	<p>1 want to start, as the other participants have, by 2 thanking the folks who put me on the agenda this year. 3 I was not one of them. I just said yes. So no 4 nepotism necessarily involved here. 5 Now, before I get to talking about Ryan's 6 excellent paper, I have to start with the standard 7 disclaimer, that the following views are solely those 8 of myself and they do not necessarily represent the 9 Commission as a whole or any of its constituent 10 commissioners. 11 Now, I want to start by just kind of doubling 12 down on some of the stuff that Ryan talked about, 13 which is this industry is exploding, right? Between 14 1980 and 2010, we had a roughly fivefold expansion in 15 the number of treatments being provided to Americans. 16 Just enormous. And if you look at the U.S. RDS data 17 which tracks, you know, the facilities providing these 18 services, you can see that since around 1990, right, 19 like where we had roughly an equal split between 20 for-profit and nonprofit facilities, that's really 21 diverged, and pretty much all of the growth has been 22 in terms of for-profits. 23 Well, you know what could explain that, maybe 24 they have much lower costs of capital, it's much 25 easier for for-profits to come in, or maybe their</p>	27	<p>1 Ryan's conclusions from the paper, you know, they're 2 doing a very straightforward analysis of like what 3 happens when a for-profit chain acquires an 4 independent, you know, in terms of the strategy they 5 pursue at that facility. It leverages just 6 preposterously sort of pipe dream, fantastical data in 7 order to do this. 8 I've played a little bit with related data 9 myself. They are great. So because of the high 10 presence of Medicare, you really see just about all of 11 the patients. Because Medicare is the overwhelming 12 payer, they're tracking stuff at the facility level in 13 a granular way that is extremely rare to encounter. 14 So just a lot of fun from a pure, you know, 15 empiricist's perspective, and the richness of those 16 data really allow us, I think, to be very confident in 17 the plausibly causal nature of the effects that Ryan 18 and his co-authors are finding. 19 And it's also just a model paper in terms of 20 performing very straightforward econometrics to get at 21 elements of interest. And the evidence, as he was 22 describing, you know, shows that patient health, 23 pretty consistently across a wide measure of different 24 outcomes, declines following these deals. And I think 25 really nicely we're able to see, by looking at what's</p>
26	<p>1 marginal profits per period are just way, way higher, 2 either maybe for some sort of socially benevolent 3 reason, lower costs, or maybe because they're -- maybe 4 they're -- maybe their lower costs are reflective of 5 lower quality, or maybe they're kind of gaming that 6 compensation system and really squeezing the -- kind 7 of the per unit compensation. That's certainly a 8 plausible story that could explain these patterns. 9 I want to put up another graph that Ryan 10 showed, which is just kind of the pattern of 11 acquisitions that's been happening over time, right? 12 So we don't just see this changing market structure 13 due to differential entry, right? We see actual 14 acquisitions by existing players of other existing 15 players. So as IO folks, we think, well, yeah, 16 obviously you can't ignore other stuff that could be 17 changing around these deals, but gosh, if we had 18 really great data, we could look within these 19 facilities to see what might be happening in them, and 20 maybe that will give us some insight into whether the 21 changing market structure reflects lower entry costs 22 or alternative behavior, kind of within each kind of 23 period, that could kind of motivate greater for-profit 24 activity. 25 And so just to kind of quickly resumm</p>	28	<p>1 going on on the clinical side, what could be 2 explaining that deterioration. 3 We can see that there appears to be shirking on 4 kind of quality inputs, and we perhaps maybe think 5 that although staying within recommended clinical 6 guidelines, maybe the excessive usage of EPO may be 7 associated with some of these negative health 8 outcomes, too, right? 9 And I think it's always nice to be able to 10 compare what we're seeing in the data to, you know, 11 qualitative stories. You know, just obviously we 12 should trust the systematic results, but it's nice to 13 be able to tell a story. And so if you just do a kind 14 of a cursory Google news search associated with fines 15 and lawsuits associated with some of the major players 16 here, well, you see a lot of stuff that says, oh, 17 these results really pass the smell test. 18 So, for example, restricting myself to just one 19 firm, in less than an afternoon's worth of Googling -- 20 or alternative search engines, no endorsement being 21 offered here -- I found, oh, this firm paid almost 22 \$400 million in terms of improper kickbacks; paid 23 almost half a billion dollars for excessive usage of 24 Venofer; paid \$55 million for excessive use of EPO; 25 almost another half billion for Zemplar; almost 100</p>

29	<p>1 million for submitting false claims. 2 At that point, I thought that's probably 3 enough; I've made my point. There's plenty of reasons 4 to think that there is worrisome quality investment 5 here by these chains. 6 So obviously I hope no one was kind of holding 7 their breath about my opinion on this paper. It's 8 fantastic. It's nice to see that it's -- that others 9 share that opinion. It's R&R at QJE. I think that 10 makes a ton of sense. It's an important topic, well 11 written, nice usage of data visualization techniques. 12 So fantastic stuff. 13 You know, because we're economists, there's 14 always things we can kind of point at and pick at and 15 suggest them to spend their time on. These were 16 things that struck me as potentially worthy of 17 additional consideration, either in this paper or 18 perhaps in a future work. 19 So one thing that struck me is I think it makes 20 a ton of sense to focus on the independent 21 acquisitions. They are cleaner in some sense, but if 22 you look inside the paper at who's acquiring these 23 independents, well, it's actually by kind of the 24 nonbig -- disproportionately by the nonbig two chains, 25 who are themselves going away over time. So that's</p>	31	<p>1 And then, of course, just given all the 2 dynamism of market activity here, just understanding a 3 little bit more about, you know, what else is going on 4 when independents are being acquired. Again, I would 5 not expect that at all to overturn the qualitative 6 results, but it would be interesting to see more on. 7 And then, again, just kind of a final nitpick, 8 extensive margin effects. You know, I think the 9 evidence is pretty clear that, on balance, there are 10 major things to worry about with some of these 11 acquisitions, but maybe there's a story to be told 12 about kind of growing the overall market with these 13 firms through outreach advertising, through outreach 14 of some other sort. It would just be nice to check 15 this out a little bit more so we can be even more 16 confident in our overall welfare conclusions. 17 So with my final 30 seconds, my big kind of 18 take-away here is, I think, what is so weird about 19 dialysis? You know, we've looked at a lot of other 20 healthcare industries, you know, we don't see 21 necessarily nonprofits behaving exceptionally 22 benevolently in the case of hospitals in particular. 23 If you think about your high-priced markets, where you 24 have quasi-monopolists operating, guess what? Those 25 are nonprofit systems.</p>
30	<p>1 kind of an odd thing. 2 It might be interesting to see, you know, is 3 there heterogeneity in there? If we focus just on 4 acquisitions by the big two, what do we see? What 5 explains why the smaller chains are going away? Maybe 6 they are, you know, less profit-minded than the big 7 two. That would be a super-fascinating thing to 8 observe. I think that there might be something there. 9 In addition, you know, I think Ryan already 10 alluded to an interesting kind of thinking about the 11 competition stuff. I think -- and I've -- candidly, 12 I've written on this, that I think there is things to 13 think about in terms of local market competition. I 14 think the stuff that the paper does is entirely 15 sensible, but I wondered about, you know, what if you 16 started restricting your attention to, you know, more 17 homogenous kind of market areas, so at least sort of 18 comparing urban areas to urban areas, and then, you 19 know, potentially endogenous measures of competitive 20 intensity to see if those results hold up. 21 So, you know, there's certainly potentially, 22 you know, no impact of local market competition, but 23 it would be nice to see a little bit more work there 24 at some point, maybe not in this paper, maybe in 25 subsequent versions.</p>	32	<p>1 There definitely don't seem to be concerns 2 about the usage of exploitation of market power in the 3 search of profits there. What is so unique about 4 dialysis that, you know, these patterns don't recur 5 or, rather, the patterns in dialysis are so starkly 6 different? 7 So I don't have any other conclusions, but I 8 would really like to see more work done to try and 9 answer that question. Thank you. 10 (Applause.) 11 MS. DUTTA: All right. Well, thanks, Nathan. 12 We are going to have about ten minutes for Q&A. 13 So I'm going to welcome Ryan back to the stage. 14 Thanks. 15 MR. McDEVITT: Are you managing the questions? 16 Are you managing them? Okay, great. 17 MR. BRUESTLE: Hi, Ryan. Stephen Bruestle, 18 Federal Maritime Commission. 19 You've done a good job of showing patients are 20 worse off and facilities are better off due to the 21 acquisitions. Any idea of whether -- and this gets to 22 one of the comments by your reviewer -- any idea of 23 whether society as a whole is better off? I realize 24 this might be a big win because you might have to rely 25 on estimates of the statistical value of life.</p>

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1 MR. McDEVITT: I think from our perspective,
2 quality has fallen considerably, which is worse for
3 society. You know, if we're agnostic about consumer
4 versus producer surplus, it's a little hard to say,
5 but if we're taking it from the perspective of
6 maximizing well-being, then clearly this is worse,
7 because patients are more likely to die, quality of
8 life is falling, and I think there's no evidence that
9 we're expanding access on that extensive margin that
10 you mentioned.

11 I don't think there's much evidence that this
12 is allowing more patients to be treated. So I think
13 from an overall societal standpoint, I think this is
14 clearly bad for society.

15 MR. BRUESTLE: (Off mic.) Well, but I also
16 would consider (inaudible) profit and more money into
17 the economy as a benefit. I mean (inaudible).

18 MR. McDEVITT: Yeah, there's not much we can
19 say in a very general equilibrium setting of, you
20 know, how does the whole healthcare system benefit,
21 but I think really what we're doing is we're
22 transferring profits from Medicare and taxpayers to
23 for-profit chains who are not making the best use of
24 these resources.

25 I think if we invested the same amount of money

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1 in other types of care, we would be much better off,
2 but I'm speculating there. We don't have a model for
3 that certainly in the paper.

4 MR. BASKER: Emek Basker, Census Bureau.

5 I'm curious about whether you have any data
6 about employee turnover or anything like that. I can
7 imagine if you're working in a facility that's
8 starting to change its practices in ways that you
9 might find very unattractive, that that would be one
10 metric of what's going on.

11 MR. McDEVITT: Yeah, a great point. From the
12 data we have, we have fantastic data, but we don't
13 have, at an employee level, who the actual employees
14 are. We have measures of, like, how many actual
15 nurses and techs are employed at the center, but we
16 don't see a turnover measure.

17 But I showed you that slide with Kent Thiry,
18 the CEO of DaVita. He thinks culture is very
19 important. He makes it a big point of all his talks
20 and all his corporate events. And I think that's what
21 he's trying to get across, is that we want to reduce
22 turnover because it affects our quality of care.

23 But another intriguing aspect of this industry,
24 the independent facilities are often owned and
25 operated by individual nephrologists, kidney doctors,

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1 and they're being bought up, and they often leave
2 right away. They're retiring or they just don't want
3 to be part of a for-profit system. And, so to speak,
4 that suggests that this is not a benevolent
5 acquisition. They're really taking over facilities to
6 increase DaVita's profits at the expense of
7 potentially, you know, employee welfare as well.

8 MR. RASMUSEN: Hi, Eric Rasmusen, Indiana
9 University.

10 Something neat about this is it looks like you
11 can maybe point to the specific places where quality
12 is going down and it matters. So you alluded to time
13 between patients and septicemia, it sounds like could
14 be caused only by that kind of unhooking and hooking
15 up, or cleaning, whereas cardiac events is kind of
16 vague. Maybe you can do more of that.

17 Also, what you find insignificantly different
18 would be important in showing not -- where not to look
19 for monitoring. And I wonder if you can see whether
20 the cardiac events are mediated by septicemia, say, or
21 not, so pin down exactly where the problem is.

22 MR. McDEVITT: I showed you a lot of results.
23 There are certainly more results in the data. These
24 are the most prominent ones, but certainly there's
25 more scope for looking into some other measures of

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1 quality.

2 I'll be frank about it, every quality measure
3 we looked at, it's worse after acquisition, except for
4 the couple that I alluded to here. We wanted to give
5 a fair and balanced picture based on what we found,
6 but everything we've looked at, patients are faring
7 worse.

8 And there are clear channels, for instance, the
9 cardiac events are clearly coming from the EPO doses
10 that are too high. We can link those directly.

11 MR. LEWIS: So you motivated this as an issue
12 of culture changing. So I'm wondering how much you
13 can say about these effects being driven by just
14 decreasing costs at the expense of taxpayers versus
15 there's also some kind of transfer of culture, you
16 know, via these acquisitions.

17 MR. McDEVITT: Yeah, I don't want to emphasize
18 culture too much. I'm sorry if I gave that
19 impression. What I meant to say is that culture is
20 just an overall part of the firm strategy, and it's
21 clear that strategy matters for these facilities.

22 And if DaVita, for instance, when they acquire
23 a facility, they're transferring their strategy,
24 culture is just one aspect of that. Probably the most
25 direct example is that DaVita/Fresenius have extensive

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1 operating manuals they give to their facilities, over
 2 100 pages, that tells you specifically what you should
 3 do in each case, what EPO dose you should have given a
 4 patient's blood levels, how long they should be on the
 5 machine, aspects like that.
 6 So those are the types of strategies we're
 7 talking about, and we can see that borne out in the
 8 data, for instance, through the length of time they're
 9 on machines or the EPO doses. That's what we can
 10 observe.
 11 MS. JIN: Can I ask a question? To what extent
 12 do you think consumers know those quality changes and
 13 still choose to stay versus they just don't observe
 14 those, or sort of it's so rare events that it sort of
 15 does not come back to them as quality and
 16 deterioration?
 17 MR. McDEVITT: Hard to say how much information
 18 consumers have. Medicare makes available what they
 19 call a Dialysis Facility Compare Website. Very much
 20 like nursing homes, you can go to the website and see
 21 measures of how the facilities compare on infection
 22 rates, hospitalization rates, some of these measures.
 23 I don't know who's accessing this and if it matters,
 24 but what we find is that consumers are not responsive
 25 at all to quality.

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1 Whether they know it or not, they just don't
 2 seem to switch facilities. Part of it is access.
 3 There needs to be an opening for them at a facility.
 4 Part of it is transportation costs, but we haven't
 5 looked at disentangling the information aspect, per
 6 se.
 7 MS. MAJEWSKI: This is Sue Majewski from the
 8 Antitrust Division, Department of Justice.
 9 I had a very related question, but typically we
 10 would be concerned about local markets and the
 11 acquisition's impact on a local market, and for that
 12 story to work, you have to have some sort of consumer
 13 substitution and some sort of signal why consumers
 14 would substitute a belief that they see some measure
 15 of quality, but I would love to see this paper sort of
 16 explore a local market angle with that.
 17 MR. McDEVITT: As I mentioned, on the
 18 summaries, we're actually working on that as well.
 19 We're very intrigued by this. The preliminary results
 20 is there's just no response to consumers from local
 21 market concentration. And I'm going to rely, again,
 22 on this story of transportation costs. They just
 23 don't switch for whatever reason.
 24 MR. GREENLEE: Patrick Greenlee also from the
 25 Antitrust Division.

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1 Do you see any patterns in terms of capacity,
 2 whether it changes post-acquisition either in the
 3 number of machines per facility or upgrades to newer
 4 technology, if there are such things? Sort of in
 5 terms of capital equipment.
 6 MR. McDEVITT: We don't have direct data on the
 7 actual machines they're using. We just have an
 8 overall count. The for-profit chains tend to have
 9 more machines per facility, and those go up a little
 10 bit after acquisition, but the issue for a facility
 11 and the standard is they just cram the facility with
 12 as many machines as they can, and then once they're at
 13 capacity, they build a new facility. It's really hard
 14 to keep adding machines.
 15 Although independents may be a little subscale
 16 from a maximizing profit standpoint, but something we
 17 don't look into, which is another intriguing feature
 18 in this industry, Fresenius is vertically integrated
 19 into the machines. They're the main manufacturer of
 20 these. So another potential paper topic, and please
 21 don't steal it.
 22 MS. DUTTA: I think we have time for another
 23 question.
 24 MR. RAVAL: So given that it doesn't seem like
 25 consumers relate to local market competition, how

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1 would you advise the regulator to change things to
 2 improve quality?
 3 MR. McDEVITT: That's a big question and a fair
 4 one given where we are today. I think I would look
 5 also at the merging entities and have that as a part
 6 of antitrust regulation. It's not just at a local
 7 level, but it's what evidence we have of how these
 8 firms implement different strategies after
 9 acquisition, and in some ways discipline them on that,
 10 and have standards, for instance, how many patients
 11 you can have per station, employees per station, have
 12 some guidelines for EPO doses, more direct measures.
 13 And that's probably outside the FTC/DOJ
 14 purview, but in this setting, that will be crucial,
 15 because competition doesn't seem to have much
 16 influence.
 17 Thank you, everyone.
 18 (Applause.)
 19 (End of session.)
 20
 21
 22
 23
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41	<p>1 PAPER SESSION: 2 NONPARAMETRIC ESTIMATES OF DEMAND 3 IN THE CALIFORNIA HEALTH INSURANCE EXCHANGE 4 MS. DUTTA: All right, thanks, Ryan, and thanks 5 everyone. 6 We're now going to move on to the second paper 7 for this morning's session, which is titled 8 Nonparametric Estimates of Demand in the California 9 Health Insurance Exchange. I'm going to invite Pietro 10 Tebaldi of the University of Chicago, who is one of 11 the co-authors on this paper, to the podium to present 12 it. 13 MR. TEBALDI: I also want to start by thanking 14 the organizers. It's great to be here and to be on 15 this program with this paper that is co-authored with 16 Alex Torgovitsky and Habin Yang, who is now a student 17 at Harvard Business School. 18 So as you can tell from the title, what we're 19 looking at here is the context of the health insurance 20 exchanges that were set up by the Affordable Care Act, 21 Obamacare, if you want, in the jargon of the media, 22 probably unnecessary in this room. This is a context 23 where, as most of you know, we have consumers who are 24 choosing a single insurance plan from a discrete -- a 25 finite set of options.</p>	43	<p>1 derive a likelihood, we estimate this model, and we 2 end up with a point estimate that we can use to then 3 extrapolate our demand curve at counterfactual prices. 4 What we do today is say, okay, we have the same 5 model. We avoided this type of parametric and 6 assumption on the indirect utility. We also consider 7 a situation where we don't let us assume that we have 8 these amazing instruments; we're moving the prices 9 everywhere. We had a finite set of observed prices in 10 the data. That means that what we're -- what we will 11 end up is a partial identification framework where 12 instead of a demand curve, I will end up with bounds 13 on the demand curve, okay? 14 Importantly, we will show that these bounds are 15 sharp, and a feature of this approach is that when 16 we're going to ask a more ambitious question, which is 17 like we move the prices in the counterfactual further 18 away from the observed ones, the method with the wider 19 bounds reflecting the higher uncertainty that we -- 20 that we are facing as a researcher. 21 A second feature that I want to emphasize is 22 that this method allow us to add assumption flexibly 23 and in a transparent way, which is as you add the -- 24 as you add stronger and stronger assumptions, this 25 will tighten your bounds, and you can see as a</p>
42	<p>1 We still have important policy questions that 2 remain at least open in some sense, and examples of 3 these questions are how would the demand respond if 4 we're changing the premiums or the premium subsidies 5 that the vast majority of these buyers are benefitting 6 from in these exchanges, and what would be the 7 corresponding change in consumer surplus? 8 Now, what we usually do -- or at least what I 9 usually do in my other work -- is combining a bunch of 10 functional form and distributional assumption that the 11 random utility that is driving this discrete choice, 12 where we think about the usual logit, nested logic, 13 maybe multinomial probit if we can make it converge, 14 or mixed logit, and then what we would ask in this 15 paper is how are our results and maybe policy 16 conclusions affected by these type of assumptions, and 17 can we make important or informative conclusions 18 avoiding these assumptions, okay? 19 So with this motivation, what we do in this 20 paper is actually consider -- I mean, to give you like 21 an overlook, right, what we usually have is this 22 common practice, we have the parameterization of the 23 random utility, we make assumption of how the 24 unobservables and the coefficients are distributed, 25 conditional on some observables (indiscernible), we</p>	44	<p>1 researcher exactly the role that is played by each of 2 these assumptions. 3 I am going to guide you through the 4 econometrics as intuitively and as parsimoniously as 5 possible, and then I will show you how we apply our 6 method to the context of the Health Insurance Exchange 7 in California and how we end up with bounds on the 8 demand changes and consumer surplus changes that are 9 quite informative, okay? 10 Now, the model is a standard one. We have 11 agents indexed by i. They make their changes from 12 this set of j option. We have the prices that are 13 collected in the usual vector P_i. We have a set of 14 observables about the consumer, the market, or the 15 goods that we collect in the vector X_i. I'm 16 introducing these market indicators. That is an 17 important piece of notation that I am not going to 18 have a lot of time to emphasize today, but you'll want 19 to think of this as the level at which your concern 20 that the unobservables about these products or these 21 markets are varying. 22 In the context of our application, this will be 23 the rating region, which is the level at which the 24 insurers are choosing how to enter in the exchanges, 25 and they're setting the network of providers and their</p>

45	<p>1 premiums, okay? For today, we model these prices, 2 these indicators, and these Xs as discrete. This is 3 just to simplify this, what we want to show. 4 We put ourselves in the situation where the 5 researcher is observing a collection of conditional 6 choices. These are the standard market shares 7 conditioned on what? Well, you will have how many 8 people are buying j, given that they're facing the 9 price b in market m and their Xs are x. We think of 10 these as being possibly constructed from individual 11 level data or observed already as market shares, but 12 here, for today, I will treat this as given from the 13 sky, go to the paper to think of the situation, as 14 always, where we're actually estimating this maybe 15 because we don't know exactly how many potential 16 buyers we have in this market, okay? 17 The consumer problem, again, is standard, and 18 this is where we introduce our main modeling 19 assumption, which is that indirect utility is 20 quasilinear in the numerator, in the price, or in the 21 premium in our application, that the date equals zero 22 is, as usual, the outside option, with the standard 23 normalizations. 24 We don't impose any restriction on the joint 25 dependence between these valuations for different</p>	47	<p>1 definitions. I'm going to get to the meat very soon. 2 In this context, right, the main unknown here is going 3 to be the distribution of these valuations, which is 4 unobserved, conditional on the prices, the market and 5 the access. We are assuming that this distribution is 6 harsh move and well behaved, which avoids us the ties 7 and a bunch of irregularities using this problem. 8 Now, what it means now that we can work with 9 this collection f calligraphic, if you want, that is 10 going to be the collection of all possible conditional 11 densities of these valuations, okay? And ideally, if 12 we know this f, we can do anything, right, in this 13 demand systems in terms of counterfactual. 14 Now, because of quasilinearity, if you give me 15 a conditional density, I can derive easily the implied 16 choices, right? Because as I said, like given 17 quasilinearity, a consumer will choose good j if and 18 only if his valuations are falling in the set. I can 19 characterize this set as a system of linear 20 inequalities. That means that the market share of 21 good j at the given prices and observables is going to 22 be the integral of this conditional density over this 23 set that I can write down exactly. 24 Now, almost there. What we care in this 25 context often, and in our paper for sure, is not the</p>
46	<p>1 goods within individual, which is we avoid to impose 2 restriction on the substitution patterns ex ante. Of 3 course, we might be concerned that these VIs and the 4 prices are dependent, and I will discuss how we want 5 to think of instruments in this context. 6 This assumption that the indirect utility is 7 quasilinear in the numerator is going to be the key 8 for us to get traction here, which is, as you know, 9 this means that now only the relative prices between 10 two goods are going to matter. An implication is that 11 if I increase all prices in the market by the same 12 amount, I'm not going to change the relative shares 13 between any pair of inside goods. 14 Now, this also means computationally that I can 15 characterize the choice problem as a solution of a 16 system of linear inequalities, and that is going to 17 give us a massive computation and identification 18 payoffs, as I'm going to show you in a couple of 19 slides. 20 A byproduct of this model is also that we have 21 a natural definition of consumer welfare because I can 22 integrate over the VIs and I have a standard -- a 23 standard utilitarian consumer surplus definition. 24 Now, in this context right there, the primitive 25 object of interest, these are just a bunch of</p>	48	<p>1 entire distribution of these valuations, but instead, 2 right, I usually have in mind a target parameter. I'm 3 calling it Theta. This could be the change in a 4 market share given a change in price, the change in 5 consumer surplus given a change in price, and so on 6 and so forth. All of these are functions of a 7 conditional density, but they don't require to know 8 the entire, density per se, unnecessarily, okay? 9 Now, imagine that I have this parameter in 10 mind, as a researcher, okay? In our case, it will 11 be the change in consumer surplus if I drop the 12 premium subsidies in the ACA by \$10 a month, okay? 13 Have that in mind. 14 Now, I have this parameter. I'm going to make 15 a bunch of assumptions on these densities, which is 16 going to restrict the set of possible densities I want 17 to consider. A standard assumption here will be a 18 bunch of my Xs are excluded, are like a good 19 instrument to think of exogenous variation in prices, 20 okay, I can call this as a restriction on these 21 conditional densities, and then, just by definition, 22 what is identified here is, well, that the density 23 that is consistent with both my assumptions and that 24 is generating market shares that correspond to the 25 observed ones, okay?</p>

49	<p>1 And now in terms of the parameter of interest, 2 the sharp identified set for this parameter is going 3 to be the image of this f^* set under this function 4 Theta, okay? This again is just a bunch of 5 definitions, but it implies that if I was able to 6 solve a very, very high-dimensional problem, and truly 7 infinite to a dimensional problem, I could 8 characterize the upper and lower bound on my parameter 9 of interest as the solution of two problems, which is 10 the mean and the max of what my parameter of interest, 11 which could be, again, the change in consumer surplus 12 in the California Exchange if I change the premium 13 subsidies, over all the possible densities that are 14 satisfying the assumption, and at the same time they 15 generate the observed market shares. We know that 16 this is true, but I personally and I don't think 17 anyone here is able to solve these problems in 18 practice because of the dimensionality. 19 So what our main idea of what we are trying to 20 do here is take this and now say, well, I can rewrite 21 this problem in a way that now is computationally 22 tractable, and it gives me the identical solution to 23 this problem on the top, okay? 24 Now, how does this work in practice? I'm going 25 to show you this with one observed price and two</p>	51	<p>1 integral where the constraint is that the density is 2 matching the observed market shares. 3 Now, how do I transform this problem in 4 something that is tractable? Well, I'm going to 5 consider this partition of the valuation space, that 6 if you notice, what I'm doing here is intercepting 7 these sets with these three sets that I had when I was 8 considering the two prices either in the data or the 9 relevant prices in the counterfactual. 10 So I'm considering this partition that has the 11 following properties, right, that within each set, 12 consumers are going to make the same choice at all of 13 the prices that are relevant to this problem. Across 14 two sets, consumers are going to make at least one 15 different choice at either the prices we observe in 16 the data or the counterfactual prices you care about 17 in your research question. 18 But now I'm going to introduce the last piece 19 of notation, which is I'm going to call "fee of L," 20 the mass that the density of valuation is placing on 21 each of these six sets. But now I can take my 22 original problem and rewrite the objective as the sum 23 of two integrals over the sets of the partition, and I 24 can rewrite that the constraints also has some of 25 integrals over the sets in the partition, and now I</p>
50	<p>1 goods, and hopefully I can give you the main 2 intuition, and then we go through the application that 3 is perhaps more interesting. 4 So here we have the valuation of good one on 5 the X axis, the valuation of good two on the Y axis. 6 I put myself in the situation where we observe this 7 price, p_a, and we're interested in what? The 8 counterfactual demand for good one, if I change the 9 price from p_a to p^*, okay? 10 Under quasilinearity, I can partition the 11 valuation space in three regions, the region of those 12 who are buying good one in yellow, the region of those 13 who choose the outside option in blue, and the region 14 of those who buy good two in gray, okay? 15 Now, the observational equivalence means that I 16 am only considering f conditional density valuations 17 that are generating the observed market share in the 18 data and they're integrating over these sets. I can 19 do the same construction for the counterfactual price, 20 okay, which means that my parameter of interest is 21 actually the integral of f over the yellow region 22 here, right, which is how many people will choose one 23 if I am at p^* and not at the observed price, p_a. 24 This is the problem that ideally we want to 25 solve, right? We want to maximize or minimize this</p>	52	<p>1 can just plug in my notation, and I end up with this 2 that is a finite linear program that I can solve 3 easily. I know I have a unique solution, and I hope I 4 convinced you that this is going to be identical to 5 the solution of the infinite dimensional problem that 6 I have up top. 7 And importantly, with engineering software, we 8 can solve these problems with many, many thousands of 9 parameters, or set of the partitions, if you want, 10 very fast and efficiently, and we know that this is 11 the unique solution to this problem, because of 12 linearity, okay? 13 So this is what we do with two prices and no 14 endogeneity issues and so on and so forth. In 15 practice, in the paper, we go over all of the math 16 that we need to extend this intuition to our general 17 case, okay? 18 I'm going to skip through a little bit. I just 19 want to say the instrument is something that we 20 typically want to be concerned about, right, so here I 21 was giving you the intuition in a world where the 22 prices are exogenous. Now, this is not an attractive 23 assumption. What we're going to do is kind of the 24 standard thing here, we're assuming that a bunch of 25 the covariates in the observables are going to be</p>

53	<p>1 excluded or orthogonal from the valuations, and this 2 is our IV assumptions, and notice that these can be 3 encoded, again, as a set of linear constraints in that 4 problem, and as long as your assumptions can be 5 written as a bunch of linear inequalities or 6 equalities, you are good to go, because you stay in 7 the world of linear programming that we can trust 8 very, very good software to give us answer very 9 quickly. Okay?</p> <p>10 I have six minutes, so I'm going to jump to the 11 application to show you some numbers. What we are 12 considering here is the California Exchange under the 13 ACA, that they are familiar with this, so I'm going to 14 move a bit quickly. We consider the subsidized 15 population, which is those between 100 and 400 percent 16 of the -- that fit our poverty level. We considered 17 the choice between the four metal tiers in the market, 18 and we have administrative data from the California 19 Exchange, and here we are considering the first tier 20 of the market, and different versions of the paper, 21 we're adding the more recent years as well.</p> <p>22 Now I'm going to jump to some figures. So in 23 practice here, I'm showing you only the bronze and the 24 silver because I can do it in a plane. These are the 25 premiums that we observe in the data. The question is</p>	55	<p>1 want, right? It's substitution patterns, and you see 2 that instead of having a point in each entry of this 3 matrix, I now have an interval, which is the sharp 4 lower and upper bound on the substitution patterns 5 that we estimate in this market. I just want to 6 emphasize that if you look at this, these bounds are 7 quite informative.</p> <p>8 In particular, in the bottom right corner of 9 this table, I can see that if we increase all of the 10 premiums by \$10 a month for all of the households in 11 the market, the enrollment probability decreases 12 between 3.3 and 8.4 percent. When you look at this 13 table carefully, you also can notice that the 14 substitution patterns do not expose IIA, which is like 15 we see in the substitution between the bronze and the 16 outside option is much higher than between higher 17 tiers and the outside option, as you would expect.</p> <p>18 If we look at different counterfactual prices, 19 which is here, I'm showing you on the X axis, the 20 change in premium for old plans in dollars per month, 21 and on the Y axis, the probability of buying coverage, 22 you see that our method, as I was mentioning earlier, 23 is going to give you wider bounds as you extrapolate 24 further away from the data, okay?</p> <p>25 So what we know here is that the demand curve</p>
54	<p>1 what happens to demand and consumer surplus if, for 2 example, I increase all of the bronze premiums by \$10 3 a month, all of the silver premiums, or both of those 4 premiums at the same time, which is equivalent to a 5 reduction in the subsidies.</p> <p>6 How do we think about identifying variation in 7 this context? Well, in the ACA, after you tell me the 8 region where you live, your household size, your age 9 and your income, your premium is a deterministic 10 function that is coming from the regulation, okay, 11 which means now if I don't want to go across 12 regions -- which I don't want to do because the 13 unobservables are varying across rating regions -- to 14 get variation in prices, I must extrapolate across 15 households with similar characteristics.</p> <p>16 So what we're doing in practice, we group our 17 households in income bins that are in six income bins, 18 as I'm showing here, and in age bins of five years or 19 smaller. The assumption in our main estimates -- and 20 then I will discuss how we can relax this somehow -- 21 is that within each region and within the intersection 22 of these income and age bins, the valuations have the 23 same distribution, okay?</p> <p>24 With this assumption, we can apply our method, 25 and the first output is an elasticity matrix, if you</p>	56	<p>1 is in between these two curves, but if I was to 2 estimate and mix logit right, I would pick one inside 3 or maybe outside of these intervals, okay? So that's 4 kind of like the main output that we're getting here.</p> <p>5 What we do then is consider consumer surplus 6 and government spending. If I think about reducing 7 all of the premiums or equivalently -- I'm sorry, 8 increasing all of the premiums or equivalently 9 reducing the premium subsidies by \$10 a month, what we 10 do here is minimize and maximize the area in this 11 figure under the data constraints in our assumptions.</p> <p>12 What we find is that, on aggregate -- I'm 13 looking at the bottom row of this table -- you would 14 save between 56 and 70 million dollars a year -- I'm 15 sorry, that you would penalize consumers between 56 16 and 70 million dollars a year, but at the same time 17 that you would save in government outlays between 440 18 million and 768 million dollars a year.</p> <p>19 This, again, is the usual finding, that if you 20 look at utilitarian consumer welfare in this context, 21 you find that we are subsidizing people that don't 22 value these goods too much. This is not a new 23 finding, and we have a whole literature who's trying 24 to explain why we see that these people, they don't 25 seem to value health insurance as we would have in a</p>

57	<p>1 standard model, okay?</p> <p>2 Now, I mentioned our assumption in terms of</p> <p>3 assuming that within these small age/income groups,</p> <p>4 the valuations don't vary. This is somewhat</p> <p>5 concerning, right, and what happens in other countries</p> <p>6 as well, you might want to relax your exclusional</p> <p>7 restriction and think of a situation in which you</p> <p>8 don't have a perfect instrument, but you might have</p> <p>9 different values of the instrument, your valuations</p> <p>10 are somewhat different.</p> <p>11 Our approach allows to deal with this, and I</p> <p>12 just want to say this before I conclude, is, you know,</p> <p>13 you could think of a world where I don't want to say</p> <p>14 that for different ages the valuations are identical,</p> <p>15 but I am willing to take a bandwidth parameter $Kappa$</p> <p>16 and say, like, as you go from 31 to 32, your</p> <p>17 valuations don't change by more than 20 percent.</p> <p>18 And, again, in this context, I can write this</p> <p>19 as a linear inequality, and I can run it through, and</p> <p>20 I can check the robustness of my estimates to the</p> <p>21 relaxation of the exclusion restriction, and I think I</p> <p>22 like this feature of what we're doing.</p> <p>23 I am out of time. I am going to leave you with</p> <p>24 this figure, where I compare our estimated bounds to</p> <p>25 your standard parametric models. Maybe this is good</p>	59	<p>1 equation that I have written out here, right? The</p> <p>2 utility from product j depends on its characteristics,</p> <p>3 that's x, and the price, that's p. We often have some</p> <p>4 unobserved quality $x(c)(j)$ and we put on a logit error</p> <p>5 term, and we take choice data, either at the</p> <p>6 individual level or market shares at the product</p> <p>7 level, we estimate by maximum likelihood, and then</p> <p>8 policymakers go ahead and use those estimates when</p> <p>9 they're thinking about merger policy or regulating</p> <p>10 markets, right?</p> <p>11 And I think there's a sort of healthy</p> <p>12 skepticism, or an understanding among practitioners</p> <p>13 that it's important to evaluate the robustness of</p> <p>14 those estimates to the assumptions that we're making</p> <p>15 along the way. So, you know, we use logit errors.</p> <p>16 What happens if we make some other assumption? Do</p> <p>17 things change if we put in brand fixed effects? if we</p> <p>18 put in interactions between consumer and product</p> <p>19 characteristics?</p> <p>20 And many of you in this room know very well</p> <p>21 some examples of these kinds of papers. I stood here</p> <p>22 two years ago maybe and discussed this terrific paper</p> <p>23 written by people in the room that used natural</p> <p>24 disasters as an instrument essentially that</p> <p>25 unexpectedly remove hospitals from local markets as a</p>
58	<p>1 because they fall inside our bounds. One thing that</p> <p>2 we noticed and that we are trying to explore further</p> <p>3 is how we tend to kind of hit the lower end of the</p> <p>4 price sensitivity compared to what our model implies</p> <p>5 could be a worst case scenario in terms of demand</p> <p>6 responses to the premium changes.</p> <p>7 And I'm totally out of time, so I'm going to</p> <p>8 leave you here. Thank you. Sorry.</p> <p>9 (Applause.)</p> <p>10 MS. DUTTA: Thank you, Pietro.</p> <p>11 So, let me welcome Kate Ho of Princeton</p> <p>12 University to discuss the paper.</p> <p>13 MS. HO: Thanks, and thanks to the organizers</p> <p>14 for putting together such a terrific conference. I've</p> <p>15 enjoyed it a lot.</p> <p>16 So I enjoyed reading this paper. Let me sort</p> <p>17 of take a big step back and out of the details and</p> <p>18 think about context here, right? So if you think</p> <p>19 about the recent literature that estimates demand,</p> <p>20 particularly in medical care, consumer demand for</p> <p>21 hospitals or for health insurers, as Pietro said at</p> <p>22 the beginning, these models are often fully</p> <p>23 parametric, right? So we assume that consumer i</p> <p>24 chooses a plan or a hospital j based on its</p> <p>25 characteristics, we write down some indirect utility</p>	60	<p>1 shock to help us evaluate these kinds of models, and</p> <p>2 that's a nice paper. I think it's R&R RAND? No?</p> <p>3 Yeah, okay.</p> <p>4 So this is the context or one of the contexts</p> <p>5 that this paper can live in. This paper is trying to</p> <p>6 take a broader view. The authors say, well, okay,</p> <p>7 let's write down this consumer indirect utility</p> <p>8 equation in a slightly more general form, or arguably</p> <p>9 a considerably more general form. We don't want to</p> <p>10 make an assumption on parametric specification or</p> <p>11 distribution of these VIJs and see how far we can get</p> <p>12 with an essentially nonparametric model, right? We're</p> <p>13 only going to assume the valuations and premiums are</p> <p>14 additively separable.</p> <p>15 So, of course, that relates to a large</p> <p>16 literature on semiparametric and nonparametric</p> <p>17 approaches to unordered discrete choice analysis</p> <p>18 dating back, way back to Manski in the seventies and</p> <p>19 Rosa Matzkin in the '90s, and these models inevitably</p> <p>20 are often partially identified. So I've written out</p> <p>21 just a few of those papers.</p> <p>22 In thinking about sort of best practice and how</p> <p>23 to think about where to put this paper in that</p> <p>24 literature, I went back and read again a paper that I</p> <p>25 wrote actually fairly recently with Adam Rosen, trying</p>

61	<p>1 to provide a survey of this literature and suggestions 2 for best practice. And it turns out that Pietro's 3 paper checks many of the boxes, so I wanted to go 4 through some of those boxes, right? 5 The paper essentially uses restrictions that 6 are motivated from economic theory, right, with 7 limited additional assumptions, and that's clearly a 8 good thing. There's an idea that crops up in this 9 literature that it might be sensible to try to place 10 bounds directly on the counterfactual values of 11 interest rather than on the underlying parameters, the 12 betas in the utility equation. 13 Why might that make sense? Well, essentially 14 because the values of interest it turns out are often 15 much simpler and easier to bound than the underlying 16 multidimensional parameters, and if you go straight to 17 the counterfactual of interest, you might generate 18 narrower bounds than if you go to the underlying 19 utility equation and then inflate things up. 20 And clearly the authors are thinking hard about 21 that kind of issue, and then their method provides 22 sharp bounds. What does that mean? Well, it means 23 that the bounds contain only parameter values that 24 could have generated the data given the assumptions 25 and no others. Well, that's clearly, you know, a</p>	63	<p>1 valuations are going to generate the same observed 2 shares for every vector of prices that we see or 3 counterfactual vector of prices that's relevant, okay? 4 And then we're going to move from the space of 5 valuations v to the space of mass functions ϕ 6 defined on those MRPs, right? Fine. 7 Then we're going to write down a familiar key 8 condition, which is the predicted shares from the 9 model equal observed shares in the data for every 10 vector of observables, and, you know, that's fine; we 11 do that all the time. And then we're going to notice 12 that because we've moved from the space v, or the 13 underlying parameters, to the space ϕ, this 14 condition now generates simple linear constraints on 15 the ϕs without throwing away any of the information 16 in the data. That's kind of a clever idea, I think. 17 Notice a couple of things. More observed 18 premium vectors provide more information, right? More 19 observed premium vectors imply smaller sets of 20 observationally equivalent valuations, hence more MRPs 21 and more linear constraints. And so intuitively, the 22 more prices we observe, the narrower the bounds are 23 going to be, and that makes sense. 24 And then we can add further conditions, 25 instruments and a vertical assumption that I won't</p>
62	<p>1 benefit in these kinds of approaches. 2 And finally, there's an idea that it's 3 important when you're using these kinds of methods to 4 explore the implications for the estimated bounds of 5 relaxing the various assumptions you've made. That 6 idea goes all the way back to Manski. Let's make very 7 minimal assumptions and look at the bounds, and then 8 let's layer on additional assumptions and see how much 9 the bounds change. And the authors do some of that. 10 I would suggest that they do more, so I'll come back 11 to that a bit later on. 12 So, briefly, how does this method work? I'm 13 going to take another stab at explaining what's going 14 on here, because Pietro didn't have a ton of time, so 15 let's see if I can make this make sense in two slides. 16 So here's the idea: Suppose consumers choose 17 an insurance plan to maximize the indirect utility, 18 right? We observe market shares of each product, 19 given prices and Xs. The authors define what they 20 call minimal relevant partitions. Remember that 21 picture Pietro put up with the shaded regions, right, 22 in different colors? These are minimal relevant 23 partitions. They have sets of valuations that are 24 observationally equivalent given the data. 25 So within each of these sets, all of the</p>	64	<p>1 talk about in detail, and then finally, we're going to 2 define our objective interest. They call it a target 3 parameter θ, preferably as a linear function of 4 these ϕ's, and the ϕ's then have to be 5 sufficiently rich in order to fully determine the 6 target parameter of interest, the change in consumer 7 surplus, or a change in market shares with a change in 8 policy. 9 And then we can place bounds on this θ of 10 ϕ, just at the lowest and highest values, such that 11 all of the linear conditions on ϕ is satisfied, and 12 notice that that's a linear programming problem. 13 There may be thousands of constraints, but still it's 14 relatively simple and it's going to generate sharp 15 bounds. So that's the idea in two slides. I think 16 it's a very nice method. 17 So some of the ideas here, of course, go back 18 to themes that are dispersed through the literature, 19 but then a lot of them are new and pretty creative. 20 The authors say in the paper that many previous 21 partially identified models deal with the unobserved 22 components of indirect utility, sort of the ϵs 23 or the Cs or these components of the $v(i)(j)$, but they 24 deal with them as a nuisance parameter, and a lot of 25 my own previous work does this. They don't try to</p>

65	<p>1 directly estimate them. They're just trying to deal 2 with them. 3 This method doesn't do that, and the authors, I 4 think quite rightly, point out that that's a benefit, 5 because policy counterfactuals also depend on the 6 distribution of these unobservables. So that's nice. 7 The method allows prices to be endogenous if 8 you can come up with instruments that you believe, so 9 that's obviously a benefit. And, by the way, the 10 authors note that relaxing the usual point 11 identification assumptions may matter, does seem to 12 matter, for policy relevant objects like the effect of 13 this premium subsidy change on consumer surplus. So 14 that's potentially important. 15 Okay, a couple of specific questions and 16 comments. So my sort of overall comment is that I 17 like the method. This paper was a tough read. You 18 know, if I were you, I would focus on making this 19 useful for empirical people, for practitioners. When 20 I read the paper for -- you know, I read it several 21 times, and even on the last reading, to me there's a 22 disconnect between Section 3, the method, the 23 econometrics, and Section 4, the empirical 24 application, right? Some of the details of exactly 25 what you're really doing are in the appendix. Some of</p>	67	<p>1 that the IV assumptions are crucial for estimation, 2 and you do a nice job of relaxing them, but I didn't 3 see -- I don't think I saw what would happen if you 4 removed them entirely. Perhaps that's in the table, 5 but, you know, in the Manski framework, starting very 6 broad and moving inwards rather than starting in and 7 moving out I think would have been useful. 8 One more slide and then I'll be out of time. 9 So overall I really think this is a creative and 10 intuitive idea. This idea of redefining the objective 11 interest in terms of objects, these phis where there 12 are linear constraints still generating sharp bounds, 13 everything gets much simpler once we're in a linear 14 world. 15 It seems to me that there are two tricky steps 16 here, right? The first is characterizing these sets, 17 these MRPs. Even in the case with only two products, 18 you know, the picture looked a little bit complicated 19 when there are many products and we've got 20 instruments, and I'm sure it's an extremely involved 21 process. 22 And then secondly -- and these two things seem 23 to me to be intertwined -- that the challenge of 24 defining a target parameter or an object of interest 25 that's preferably a linear function of these phis,</p>
66	<p>1 them are not anywhere, I don't think. 2 If I were you, I would take this estimation 3 section, which I had to read through to Appendix G to 4 find, put it in the paper, right, use up a page of 5 text and just lay out a menu for practitioners exactly 6 what are the equations you're using for estimation. 7 Put in more explanation. 8 Some of these results are super-important, I 9 think, about the impact of these policy changes on 10 government spending, for example, and I needed more 11 explanation of exactly how you got there. And then 12 you can discuss how to generalize, relaxing the IV 13 assumption, which you do very nicely. 14 Can you allow for horizontal differentiation? 15 What if you put in brand effects, how would that 16 change the method? And the kinds of issues that 17 practitioners are going to care about. 18 And then sort of thinking back to my slide on 19 best practice, I think it's super-important in this 20 literature to explore the implications of relaxing the 21 assumptions for the breadth of the estimated bounds. 22 And certainly there's some of that in the paper, but I 23 would have liked to have seen more. 24 So what happens if the vertical structure 25 constraints are removed or relaxed? It's pretty clear</p>	68	<p>1 right? And it would be great if you could say 2 something more about broader applications with these 3 challenges in mind. 4 So what other target parameters could be 5 assessed using this method? Did you have to very 6 carefully pick this target parameter in order for it 7 to fit into the methodology? It seems to me there's a 8 tradeoff between, you know, defining an interesting 9 counterfactual versus needing a large number of MRPs 10 in order to determine it and that part of the process 11 being implausible. I may be wrong about that, but it 12 would be great to see more discussion of that issue. 13 And then going back to what I said on the 14 previous slide, so you're characterizing sharp bounds, 15 and in the results that are also informative, exactly 16 which assumption is it that makes them informative? 17 And as you change the assumptions, how much do the 18 bounds change? 19 But overall I think it's a terrific paper. I 20 think it's going to have some real impact. Really, my 21 only comment is make it easier for us to understand so 22 that we can actually use it. 23 Thanks a lot. 24 (Applause.) 25 MS. DUTTA: All right. Thank you, Kate.</p>

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1 So we can have ten minutes again for Q&A.

2 AUDIENCE MEMBER: So I think the assumption
3 that the functional Theta is linear, you need to have
4 that to get a connected, sharp identified set. Is
5 that where you're actually using it, or is it bringing
6 you more?

7 And related to that, what kind of -- with this
8 linearity assumption, what kind of target parameters
9 are you actually excluding?

10 MR. TEBALDI: Sorry. So the first one.

11 AUDIENCE MEMBER: So the first one --

12 MR. TEBALDI: No, no, no, I remember. So the
13 first part is do you need a linearity for the
14 sharpness, the answer is no.

15 AUDIENCE MEMBER: For the connectedness of the
16 sharp identified set.

17 MR. TEBALDI: So you can look at it -- so if
18 you look in the paper, what we show is first how you
19 transform the problem in the finite problem. In that
20 problem, you know that the problem is regular, and it
21 gives you a connected set.

22 Now, however, what we cannot -- so the key here
23 is that to transform the problem into the finite
24 problem, you need functions that only vary with the
25 mass over the MRP, okay? And that's the key here

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1 because -- I mean, obviously, like, if I transform the
2 problem in a problem that only depends on the mass,
3 the objective function needs only to depend on this
4 mass.

5 That restricts us -- and if you think about it,
6 if you ask a question that depends on anything more
7 than that, which is the heterogeneity within these
8 sets, there is nothing in the data that can possibly
9 tell you that, right, because the definition of the
10 partition is such that all the information that you
11 have in the data is contained in this problem, which
12 is -- in some sense you're limiting yourself to target
13 parameters where you possibly have information in the
14 data.

15 Now, what this allowed us to do is the demand
16 stuff that I showed, I saw like the counterfactual
17 choice shares and things alike, the consumer surplus
18 changes, and similar other problems. What it doesn't
19 allow us to do is anything that has to do with
20 integrating within the sets of the partition, and we
21 can come up with a lot of these questions of interest.

22 AUDIENCE MEMBER: I guess I just didn't
23 understand the requirement that the target parameter
24 is linear and the -- the one phi I guess.

25 MR. TEBALDI: Linearity means that I can write

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1 it as an integral over sets of the partition, and that
2 means that if I'm integrating over a specific
3 function, I need to assume that this function is known
4 ex ante. And like in the case of the market share,
5 it's an indicator function; in the case of the
6 consumer surplus, we know how to write it down.
7 That's kind of the answer.

8 MR. LEWIS: Is it possible to pull up your
9 slides?

10 MR. TEBALDI: I don't know. I have very little
11 control.

12 MR. LEWIS: So I was wondering if we can get
13 the slides up, and if you can show that graph of the
14 partitions, and just walk through the intuition
15 about -- so the intuition of you had the division of,
16 you know, don't buy anything, buy good one or buy good
17 two.

18 MR. TEBALDI: Yeah.

19 MR. LEWIS: And then you had the further
20 partitions, and I was wondering if you could just walk
21 through that and explain how that relates to the
22 consumer surplus question.

23 MR. TEBALDI: Oh, how do we deal with the
24 consumer surplus question?

25 MR. LEWIS: So you're using this partition to

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1 specifically get at the issue of what is this target
2 parameter of interest.

3 MR. TEBALDI: Yeah, yeah, yeah. So actually
4 it's related to --

5 MR. LEWIS: And so how did you draw those
6 partitions such that that answers that question?

7 MR. TEBALDI: So the partition is not -- okay,
8 so let me go here, right? So the partition really
9 doesn't depend on the question. The partition is
10 going to depend on the prices you observe in the data,
11 in this case only one, P_a , in blue, and the prices
12 that you care about in the counterfactual, which is p^* ,
13 okay?

14 And this is -- the partition only depends on
15 the prices you consider. If you give me a set of
16 prices, I end up with this, which is as I cross
17 between two sets, at least one of these price's agents
18 are going to make a different choice, okay? And if I
19 stay within a set, at all of the prices that are
20 relevant to this problem, consumers are making the
21 same choices, okay?

22 MR. LEWIS: Right. So the idea is -- so the
23 V_2 , for example, is saying that both in the world with
24 p_a as well as in the world of p^* , people who are in
25 that V_2 area are making the same choice regardless?

73	<p>1 MR. TEBALDI: Yeah, and they are going to</p> <p>2 choose good one at p_a and they're going to switch the</p> <p>3 outside option at p^*. These guys in V_1, they're going</p> <p>4 to stay in the outside option at both prices, and we</p> <p>5 can go over all of these.</p> <p>6 MR. LEWIS: I see.</p> <p>7 MR. TEBALDI: Okay? Now, for the consumer</p> <p>8 surplus, you realize that when we go from p_a to p^*, we</p> <p>9 should take the integral over all of these Vs within</p> <p>10 V_4 maybe, okay? And this is answering maybe your</p> <p>11 question, but that's where you go back to the drawing</p> <p>12 board and you realize that to characterize the upper</p> <p>13 and lower bound of consumer surplus, within each set</p> <p>14 of the partition, I can place all of the mass at the</p> <p>15 extreme points at either the southwest or the</p> <p>16 northeast point for the consumer surplus. For the</p> <p>17 demand changes, I don't need to do any of that. It's</p> <p>18 kind of hard without the slide.</p> <p>19 AUDIENCE MEMBER: Pietro, thanks. I was going</p> <p>20 to ask how you deal with derivatives, because all</p> <p>21 these are integrals, but I guess when you have enough</p> <p>22 price changes, these little phis are going to be over</p> <p>23 small enough grid points that you're going to look</p> <p>24 at -- like elasticities, right? These are</p> <p>25 derivatives.</p>	75	<p>1 thanks, everyone. We're going to take a short break</p> <p>2 and be back here at 11:00 for the keynote address.</p> <p>3 (Applause.)</p> <p>4 (End of session.)</p> <p>5</p> <p>6</p> <p>7</p> <p>8</p> <p>9</p> <p>10</p> <p>11</p> <p>12</p> <p>13</p> <p>14</p> <p>15</p> <p>16</p> <p>17</p> <p>18</p> <p>19</p> <p>20</p> <p>21</p> <p>22</p> <p>23</p> <p>24</p> <p>25</p>
74	<p>1 MR. TEBALDI: Yeah.</p> <p>2 AUDIENCE MEMBER: What you're identifying are</p> <p>3 integrals or -- but I guess you're looking at small</p> <p>4 changes, and if you have enough prices, with small</p> <p>5 enough cells, that's how you do -- you know,</p> <p>6 elasticities?</p> <p>7 MR. TEBALDI: Oh, so actually what we do here</p> <p>8 is change in shares, and you're right that we often --</p> <p>9 we want to transform these in the same elasticity or</p> <p>10 elasticities. So for the -- we didn't think about</p> <p>11 this idea of observing a small change in price, and we</p> <p>12 could do that if you want to then interpret it as an</p> <p>13 approximation of an elasticity.</p> <p>14 What we did think about and we are trying to</p> <p>15 work it through is there is a -- this part of linear</p> <p>16 programming that is called fractional linear</p> <p>17 programming, where even if you don't have a linear</p> <p>18 objective function, that you can deal with ratios and</p> <p>19 keep the sharpness. This is something that goes a</p> <p>20 little bit beyond my contribution to the paper, but</p> <p>21 you can deal with same elasticity and elasticity in</p> <p>22 this formal way, but it's a good idea that if I had</p> <p>23 small variation in prices, I could do this as an</p> <p>24 approximation, just directly using our method.</p> <p>25 MR. DUTTA: So I think we're out of time. So</p>	76	<p>1 KEYNOTE ADDRESS, "OWNERSHIP CONCENTRATION</p> <p>2 AND STRATEGIC SUPPLY REDUCTION"</p> <p>3 MS. DUTTA: All right. Welcome back, everyone.</p> <p>4 So I have the great pleasure of introducing</p> <p>5 this morning's keynote speaker, Dr. Katja Seim, who is</p> <p>6 an Associate Professor of Business Economics and</p> <p>7 Public Policy at the Wharton School. She is also a</p> <p>8 member of our scientific committee this year.</p> <p>9 Dr. Seim's research has been published in a</p> <p>10 number of leading journals, including American</p> <p>11 Economic Review, the RAND Journal of Economics and</p> <p>12 American Economic Journal-Microeconomics. Her</p> <p>13 research primarily focuses on two broad areas in</p> <p>14 empirical industrial organization, which are product</p> <p>15 introduction and entry decisions by firms, and price</p> <p>16 discrimination and nonlinear pricing, especially in</p> <p>17 the context of the communications and information</p> <p>18 industries.</p> <p>19 In addition to her research and academic work,</p> <p>20 Dr. Seim has also served as the Chief Economist at the</p> <p>21 Federal Communications Commission. Dr. Seim's keynote</p> <p>22 address today is titled Ownership Concentration and</p> <p>23 Strategic Supply Reduction. Please join me in</p> <p>24 welcoming Dr. Katja Seim.</p> <p>25 (Applause.)</p>

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1 MS. SEIM: All right. Thank you very much for
 2 having me, including me on the program and asking me
 3 to contribute. Oftentimes I think when you're asked
 4 to give a keynote address, all of a sudden you feel
 5 very old, and I wasn't quite prepared to feel so old.
 6 So I decided to use my time today to actually talk
 7 about a project of mine that I have been working on
 8 again pretty actively rather than giving you a more
 9 general talk about the state of the literature.

10 This is a paper we've worked on for a while and
 11 are about to hopefully wrap up again pretty soon. So
 12 suggestions and comments would be very appreciated.
 13 It's joint with a number of people who always were
 14 colleagues of mine at Penn but have mostly moved on
 15 since, Ulrich Doraszelski, Mike Sinkinson and Peichun
 16 Wang. The paper broadly looks at the role of market
 17 power by TV broadcast stations in the recently
 18 completed spectrum auction that the FCC ran that is
 19 called the incentive auction.

20 And so before telling you a little bit about
 21 the details of what we do, I also wanted to say that I
 22 was very fortunate to spend some time at the FCC, like
 23 Antara said, during the time that we spent on this
 24 project, and so I should probably actually have the
 25 disclaimer that other government people have on their

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1 slides, but most importantly, I think for our
 2 purposes, it's really been helpful in helping us
 3 understand the auction and being able to draw on
 4 experts who understand it even today, I think, much,
 5 much better than we do. And so I was really grateful
 6 for all of the support we got there.

7 So in motivation, let me just talk a little bit
 8 about the types of issues the FCC faced and what they
 9 attempted to do. As I think we can all agree, the
 10 biggest resource, the FCC allocates its spectrum,
 11 which is scarce and maybe increasingly valuable, and
 12 one problem that then arises is that we have lots of
 13 allocations of spectrums for two types of services
 14 that historically were very intensively used but are
 15 maybe less intensively used today.

16 The biggest such service is broadcast
 17 television, which is over-the-air TV. Today probably
 18 less than 10 percent of households use over-the-air TV
 19 to access programming. Nevertheless, as this slide
 20 shows you, significant amounts of spectrum, even
 21 today, are dedicated to broadcast TV transmission.

22 And so what you see here in this slide is
 23 basically two portions of the band plan that is set
 24 aside for broadcast television. The lower portion,
 25 which is allocated to VHF, low intensity services, we

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1 will not talk much about. We are going to focus on
 2 the upper portion of the band plan, which is allocated
 3 to UHF TV channels. That has shrunk over time because
 4 of the digital transmission introduction by these
 5 stations, but even as of today, we have set aside
 6 spectrum for 37 different UHF channels in several
 7 markets, and that spectrum occupies space that we
 8 might think could be more efficiently used by other
 9 service providers, in particular cellular and wireless
 10 providers.

11 And so what I have shown you, then, at the
 12 bottom is what the band plan hopefully will look like
 13 by 2020 when the amount of spectrum to UHF channels
 14 has shrunk from 37 to 23 channels, with the remainder
 15 of the spectrum moving to wireless providers.

16 And so, you know, what we look at in this paper
 17 is how might you facilitate this kind of transition of
 18 spectrum allocation and to what extent do individual
 19 firms that own multiple broadcast TV licenses
 20 interfere with how that process works.

21 The challenge that we face in facilitating that
 22 kind of transition is twofold. The one on the TV side
 23 spectrum is very fragmented. In ownership, there's
 24 about 2000 full-power TV stations today that have
 25 market areas that did not line up at all with the

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1 wireless market areas, and so here in this slide you
 2 can see the contour of ABC New York and the market
 3 area that it serves, that has very little to do with
 4 the type of market that a wireless provider typically
 5 thinks about.

6 At the same time, then, what we want to think
 7 about is, you know, in allocating a spectrum, how we
 8 incentivize TV broadcasters to give up their spectrum
 9 voluntarily and re-allocate it to wireless users who
 10 will hopefully use it more efficiently. The FCC
 11 decided between 2016 and '17 to run what they called
 12 an incentive auction. It's really unique in a number
 13 of ways. Most importantly, it's the first auction
 14 that they have run where they both bought up spectrum
 15 and then turned around and resold that spectrum at the
 16 same time.

17 The paper here is going to focus on that
 18 initial buy-up process, which is called a reverse
 19 auction. The second portion of it of then turning
 20 around and selling the spectrum in the mobile market
 21 is the forward auction. These two interact in that
 22 the biggest challenge the FCC faced in the auction is
 23 that it needed to reduce the amount of spectrum
 24 allocated to TV broadcasters before turning it over to
 25 mobile broadband service and do what they call

81	<p>1 repacking stations into a smaller portion of the 2 spectrum band plan. 3 So, you know, the way this worked -- and, you 4 know, if you take away one thing from the 5 presentation, I think it is that this is an extremely 6 complex process that I think the FCC deserves a lot of 7 credit for having pulled off in a very smoothly 8 running auction. What needs to happen is that a 9 station who currently broadcasts on, say, channel 45, 10 and does not want to give up its spectrum in the 11 auction, needs to be artificially moved down to the 12 portion of the spectrum that continues being TV 13 broadcast spectrum, so say channel 27. 14 The FCC does have the right to move stations, 15 even though they don't have the right to force 16 stations to give up their spectrum, but they can only 17 move a station as long as that move limits the amount 18 of additional interference that the station faces to 19 less than 0.5 percent of its current ownership. 20 And so, you know, that basically means that I 21 can move you to a channel as long as the amount of 22 population that you are serving after that move is 23 extremely similar to what you were serving before. So 24 that is going to introduce a bunch of constraints on 25 who can be located next to each other in the spectrum</p>	83	<p>1 reflected two things that resulted in stations being 2 differentiated. One, it reflected the station's 3 population reach as a measure of how attractive the 4 station was to viewers. And then two, it reflected 5 how difficult the station was to be repacked should it 6 choose to stay on the air and that they proxied for by 7 the number of other stations that the station could 8 not interfere with were it to stay on the air. 9 So these interference constraints basically 10 tell you, you know, if you stay on, how difficult is 11 it for us to fit you into that remaining amount of 12 spectrum, and as a result, if you're really difficult 13 to fit, we want to incentivize you to actually sell 14 out. And the broadcast volume reflects that. 15 So then think about the strategy. The nicest 16 thing about the Milgrom and Segal descending clock 17 auction format is that if you own a single license in 18 that setup, it's weakly your dominant strategy to bid 19 your value. In our context here, because of this 20 relationship between the nationwide base clock price 21 and your broadcast volume, that basically means you 22 stay in the auction until the nationwide clock price 23 drops below your valuation adjusted by your broadcast 24 volume. 25 And everybody follows that strategy in</p>
82	<p>1 plan. 2 And so the biggest challenge, then, with the 3 incentive auction is that what their goal was not only 4 to identify the lowest cost set of stations that they 5 wanted to purchase to acquire a certain amount of 6 spectrum, but it was a constraint problem in that 7 whoever chose not to sell out needed to be repacked 8 into the remaining channels. 9 And so if you then think about, you know, this 10 repacking problem, there's many combinations of 11 stations that could potentially remain on the air 12 after the auction, and that in terms of a feasibility 13 checker is the biggest computational issue with the 14 auction. It means that every stage of the auction 15 computationally checked that whoever is left can still 16 continue broadcasting. 17 The way the auction worked is you should think 18 of it as a descending clock auction. It was developed 19 by Milgrom and Segal and was operationalized through a 20 nationwide base clock price that we've called capital 21 P here, but that clock price was translated into an 22 individualized price for every station as a function 23 of what they called the station's broadcast volume 24 fee. 25 The station's broadcast volume fee simply</p>	84	<p>1 equilibrium, and we can, therefore, then identify how 2 expensive it would be to buy up a certain amount of 3 spectrum that would then be turned around to the 4 forward auction, and we can figure out what would 5 wireless companies be willing to sell to purchase that 6 spectrum. And if their willingness to pay does not 7 exceed what the broadcasters need to get to sell off 8 that spectrum, we would lower the amount of spectrum 9 and continue; otherwise the auction is going to close. 10 Now, this works nicely if there's single 11 owners, every station is owned by a single company. 12 What we're interested in in the project is what the 13 role of multi-owners might be who own basically chains 14 of broadcasters who own several stations and might 15 have the ability to strategically interfere with how 16 efficiently the auction works. 17 There's multi-license ownership for two 18 reasons. One is purely historical accident. The FCC 19 is typically concerned about market power in the 20 advertising market in a local market, so there's 21 constraints on which types of stations you can own 22 jointly. You can't own ABC and CBS, for example, but 23 there's typically much less concern about you owning 24 multiple independent stations that are not very 25 valuable, but are valuable from a spectrum perspective</p>

85	<p>1 if you were having concentration.</p> <p>2 How we got interested in the project is that</p> <p>3 after the announcement of the auction, we also saw a</p> <p>4 lot of buyouts of largely failing stations by private</p> <p>5 equity firms, which amassed significant spectrum</p> <p>6 holdings, and I've just here shown you a bunch of</p> <p>7 listings for one of the three companies that were</p> <p>8 concerned, NRGTV.</p> <p>9 So you can see that they bought out a whole</p> <p>10 bunch of stations, most of them are on the coast, not</p> <p>11 particularly successful stations from a broadcast</p> <p>12 perspective, but potentially quite valuable from a</p> <p>13 spectrum perspective. This drew a lot of attention</p> <p>14 from a speculative perspective and resulted in, you</p> <p>15 know, for example, bidding wars for what were nearly</p> <p>16 bankrupt stations.</p> <p>17 The trade press focused on flipping of these</p> <p>18 stations, which isn't necessarily an efficiency</p> <p>19 problem. We're also going to think about the possible</p> <p>20 role that strategically you might have from owning</p> <p>21 multiple stations. So this gives you sort of an</p> <p>22 overview of these three private equity firms which</p> <p>23 attracted a lot of the attention, this NRJ, OTA and</p> <p>24 Locust Point. They bought up, up until the onset of</p> <p>25 the auctions, about 44 licenses, but you should keep</p>	87	<p>1 And so we do three things in the paper, and I</p> <p>2 don't think I will really talk about very much of any</p> <p>3 of these, but we first develop a simple model of the</p> <p>4 reverse auction that gives you a sense of when you</p> <p>5 might want to successfully withdraw a license from</p> <p>6 participation, to think about, you know, how you can</p> <p>7 exploit the fact that you own multiple stations, but</p> <p>8 then going to try and quantify the possible</p> <p>9 contribution of such behavior to the auction or</p> <p>10 auction's outcome by first estimating reservation</p> <p>11 prices for all of the participation stations, and then</p> <p>12 quantifying the impact of strategic bidding using a</p> <p>13 large-scale simulation of what would have happened in</p> <p>14 the auction had such strategic behavior been</p> <p>15 important.</p> <p>16 So we are going to do this both for the initial</p> <p>17 clearing target that the FCC announced of freeing up</p> <p>18 126 megahertz of spectrum and the one that was then</p> <p>19 finally realized of freeing up 84 megahertz. So to</p> <p>20 give you a little bit of intuition on the model side,</p> <p>21 I wanted to make sure you understand how repacking</p> <p>22 works and how that affects our findings. Let me move</p> <p>23 on to that first.</p> <p>24 And so to think about how repacking works and</p> <p>25 how it interacts with strategic behavior by firms,</p>
86	<p>1 in mind that this is only a small fraction of the</p> <p>2 multi-license ownership that we see, the remainder</p> <p>3 largely being that way before the auction even was</p> <p>4 announced.</p> <p>5 And so what we then want to think about in the</p> <p>6 paper is what the incentives might be for these firms</p> <p>7 to strategically withhold licenses from the auction.</p> <p>8 We are going to think about, you know, your ability to</p> <p>9 affect the base clock price and the price at which you</p> <p>10 might sell other licenses that you own as potentially</p> <p>11 affected by your decision to bid or not bid in all of</p> <p>12 the licenses that you have.</p> <p>13 And so this is going to be similar to the types</p> <p>14 of strategic supply reduction effects studied in the</p> <p>15 electricity markets. So Ali, for example has done</p> <p>16 some work there, but I want you to keep in mind, in</p> <p>17 terms of how we're different, it's basically that A</p> <p>18 units are discrete, and we don't see firms bidding</p> <p>19 supply schedules, but maybe more importantly, TV</p> <p>20 stations are not a homogenous product because of the</p> <p>21 way they interfere with each other, which isn't</p> <p>22 necessarily the case in electricity markets, and so</p> <p>23 it's a nice setting to think about what the role of</p> <p>24 product differentiation might be on your ability to</p> <p>25 move prices in these types of settings.</p>	88	<p>1 we're going to think about clearing 126 megahertz of</p> <p>2 spectrum, going to leave us about 16 channels that</p> <p>3 stations who do not want to sell out can move to. A</p> <p>4 stations's decision if they bid naively based on just</p> <p>5 single individual station behavior is they're going to</p> <p>6 stay until the clock price falls below their value as</p> <p>7 operating a TV station.</p> <p>8 If the station withdraws and chooses not to</p> <p>9 sell, it then needs to be repacked into that lower</p> <p>10 portion of the spectrum. The system is going to</p> <p>11 verify that all of the remaining stations could also</p> <p>12 repack should they choose to withdraw later in the</p> <p>13 auction. And if a station cannot be repacked, it</p> <p>14 would then be labeled as a winner of the auction.</p> <p>15 This is going to continue until all of the</p> <p>16 licenses are repacked or are winning, and the auction</p> <p>17 is then going to conclude. We give you an example of</p> <p>18 Philadelphia. We like Philadelphia for a number of</p> <p>19 reasons, one of them being that strategic supply</p> <p>20 reduction is really only important in large markets</p> <p>21 where wireless demand is high. Philadelphia is one of</p> <p>22 them.</p> <p>23 And so what I'm showing you here is</p> <p>24 interference constraints for a station in central</p> <p>25 Philadelphia, NBC Philly. In that, we show you</p>

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1 adjacent channel constraints, stations that cannot be
2 located right next to Philadelphia in the channel
3 lineup, and then in yellow we have stations that
4 cannot be located on the same channel.

5 So this is where we start. For example, today,
6 we have here the current set of channels before the
7 auction. We've shaded in light blue the ones that are
8 currently occupied by stations, each of which have six
9 megahertz of spectrum, and what we want to do is take
10 these stations -- some of them are going to go off the
11 air, some of them want to continue -- and squish them
12 into that smaller portion of the spectrum.

13 So, for example, the clock price is going to
14 tick down, tick down, starting at 900, and initially
15 not everybody stays in the auction. The price is high
16 enough that they would prefer to take it as opposed to
17 leaving. Then, say, we hit a clock price of 600. At
18 that point, the first station withdraws. In Philly,
19 the most valuable is CBS Philadelphia. They choose to
20 exit the auction and continue as a broadcast station.

21 At that point, when only CBS is there,
22 everybody else is currently still active, could still
23 fit in that smaller portion of the band plan, the
24 clock ticks down to 550. Now NBC goes out of the
25 auction. Everybody else can still be repacked. Fox

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1 drops out at 500, and then we're going to hit 450.
2 MyNet is out. Everybody else can still be repacked.

3 Now we hit 400, and when we hit 400 and
4 Univision decides that they would prefer to continue
5 operating, holding onto their license rather than
6 taking that price, is actually going to go out, but at
7 this point there are three stations that -- with the
8 existing five stations that continue operating could
9 no longer fit in that band plan.

10 So at this point, the FCC is going to deem
11 these stations as conditionally winning, and they
12 would get, in terms of price, the price at which
13 Univision, the last station, would go out, so it's a
14 clock price of 400.

15 And then the process continues, and we're going
16 to keep going until all of the stations either have
17 chosen to exit the auction, because the clock price
18 has fallen too much, or can no longer be repacked, in
19 which case they are conditionally winning.

20 So, you know, then think about how strategic
21 supply interaction works here. If you are a single
22 license owner, you just follow your dominant strategy,
23 and it's a second price auction where the price that
24 you get is set by the firm that leaves just before
25 you.

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1 For a multi-license owner, we are going to
2 think about what would happen if you considered the
3 following strategy. You have, say, two licenses. You
4 can consider to take one out and simply bid the other
5 one at the naive strategy off the value, in which case
6 withdrawing the first one can help you for total
7 payoffs for two reasons.

8 One, it might mean that your other station no
9 longer can be repacked and becomes a winner at a
10 higher price; or two, it could be that by you not
11 participating, there's a different station that sets
12 your station's price that might also be better.

13 We developed the theory in the paper a little
14 bit. None of us are auction theorists, so that's one
15 small problem, but we can show that this strategy of
16 either withdrawing a station and continuing to bid at
17 value for the other one that you have is a weakly
18 dominant strategy for these strategic bidders.

19 So let me just give you an example and then
20 I'll show you our results. So think about you being a
21 TV broadcaster that owns two licenses in a market, a
22 and b. These licenses are in a market where the FCC
23 plans to buy K licenses, and we've ordered the
24 licenses by the drop-out point, which is the value
25 adjusted by the broadcast volume.

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1 Now think about the case where both of these
2 two stations that you own have, in terms of their
3 score value of a broadcast license, a score such that
4 they are within the set of K stations that should be
5 bought. And under naive bidding, where everybody bids
6 their value, the K+ first station would set the price
7 for all of them.

8 In that case, the firm's profits is going to be
9 what it gets back in the auction, which is the base
10 clock price of the K+ first station, scared up by
11 broadcast volume, minus the value that they give up
12 the profit from being a broadcast station.

13 In contrast, if they decided to withdraw one of
14 the licenses, that might give them higher payoffs
15 because we've now raised the closing clock price to be
16 the score of the K+ second station, and our firm is
17 now going to, in terms of outcomes, make profit on the
18 late license b, which it sells, and hold onto license
19 a, which has outside payoff value.

20 And so that's going to be profitable if the
21 payout increases on license b, which it continues to
22 sell, exceed the cost of no longer selling station A.
23 And so if you think about then what types of stations
24 qualify there, the opportunity costs of not getting
25 rid of one of your stations is going to be low if that

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1 station is very profitable in the broadcast market --
2 that's what we call VA -- or if it has relatively low
3 broadcast volume and can be repacked easily in the
4 auction. And so that's sort of the types of tradeoffs
5 that we evaluate in this simulation.

6 I should say this is a very complicated problem
7 and with a nationwide system totally infeasible, so we
8 do not attempt to make any such calculations.
9 Instead, what we're going to consider is a situation
10 that multi-license owners are strategic only in the
11 market in which their license is, so in one DMA, and
12 then we're going to also simplify this repacking
13 system to be only applicable to the DMA itself and an
14 area around it.

15 And so I sort of have some numbers that
16 hopefully suggest that this is computationally
17 complicated and tell you why we've been working on
18 this for a long time.

19 Now, we're going to estimate reservation
20 values -- I won't have much to say to that -- to be
21 then able to quantify the value of strategic bidding.
22 We basically use a cash flow model that is used by the
23 industry as well to think about what the station's
24 value going into the auction would be and what they
25 would be giving up were they to surrender their

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1 license.

2 One thing I should say is that this is unusual
3 in the auction literature, that typically we rely on
4 the model to give us optimality conditions, and we use
5 that to back out the value that the station would have
6 to have to be consistent with the actions that they
7 take. We choose to do the reverse and start with an
8 estimate of reservation values, and probably not a
9 very good one, but we do that for the following
10 reason.

11 In our case, the only data that we have about
12 the auction and its outcome is the set of stations
13 that sold and the price at which they sold. We do not
14 know who participated and we do not know what the
15 bidding behavior would be of a station that was frozen
16 and how much further they would have been willing to
17 stay in the auction had they not been frozen out.

18 And so the data that we have we feel is not
19 particularly informative, even though I want you to
20 keep that in mind when you think about what we do then
21 in terms of estimating reservation prices directly.

22 So let me show you an example from Philadelphia
23 and then the final overall results to illustrate what
24 we do. This is our estimates of reservation values in
25 Philadelphia. And maybe not surprisingly, they line

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1 up pretty closely with advertising revenue that these
2 stations can make. That's their main source of
3 revenue and their main source of profit.

4 I want you to see that for the most part we see
5 really skewed distributions. There are some stations,
6 like the big ABCs, CBSs of the world that are very
7 valuable. There's typically a large tail of stations
8 that have very little value in the broadcast market.

9 Okay. Now looking at naive bids, we've
10 overlaid your naive bids here, how long would you stay
11 in the auction if you just bid your valuation. You
12 can see that that also lines up nicely with the values
13 but departs sometimes because your value in the
14 auction also reflects your broadcast volume and not
15 just your reservation value. And so that is, in
16 particular, important for some of the low-value
17 stations that interfere with a lot of others to
18 actually be quite valuable in the auction itself.

19 Then we want to look at what that would look
20 like under strategic behavior. We're going to
21 simulate strategic outcomes using some of the FCC's
22 own software to check whether stations can be
23 repacked, and then use that to compare payouts under
24 strategic bidding to payouts under naive bidding.

25 So, you know, we're going to repack the DMA

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1 neighborhood like that, and in Philadelphia, then,
2 this is what this is going to look like. Starting
3 with the same chart as before, we have reservation
4 values in blue, the naive bids as crosses, and then in
5 dark blue the payouts that the stations received that
6 were able to sell.

7 Now looking at how that changes under
8 strategic, what I want you to focus on is two sets of
9 multi-license owners in Philadelphia, and we're going
10 to think about their payoffs should these two stations
11 withhold one station each from the auction, at which
12 point now their bids would be the same as before,
13 except for they would ramp up the bids on these
14 stations that they withdrew to just not be in the
15 auction at all.

16 And so then what I've overlaid here is their
17 payoffs under strategic bidding, and there's two
18 things I want you to see. Strategic bidding here
19 benefits the individual stations that withdraw their
20 licenses from the auction, so that's the first thing.
21 That just means that for them, it was individually
22 profit-maximizing to do that. But they also impose a
23 large externality on the other stations in the market
24 that are single owners in that you can see that
25 payouts increased across the board for the stations

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1 that sold. And so one reason why we find big payout
 2 increases is simply because there's this externality
 3 that strategic behavior benefits not just the firm
 4 itself, but everybody.
 5 So I would show you the main results, and then
 6 I wanted to talk a little bit about how this compares
 7 to the actual auction outcome. There's a lot of
 8 numbers here, not all of which are important for what
 9 I wanted to show you. The main numbers that we take
 10 away from this is if we compare this naive bidding --
 11 the everybody bids value -- to strategic bidding, we
 12 see that under the initial large clearing target of
 13 126 megahertz, payouts would increase by 22 percent.
 14 Under the smaller clearing target that was
 15 ultimately realized of 84 megahertz, we still see that
 16 strategic behavior increases payouts by 7 percent to
 17 the firms, and that is true across the board, both for
 18 single and for multi-license owners.
 19 There's a number of caveats that we look at in
 20 the paper. There's two that are important. The first
 21 one is in our simulation so far, we've assumed that
 22 everybody participates in the auction. In practice,
 23 there were significant concerns about whether
 24 especially religious and nonprofit stations would
 25 actually choose to participate, and so we've redone

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1 this under reduced participation and find, maybe not
 2 surprisingly, that the payout increases from strategic
 3 bidding go up very significantly, both for the 126
 4 clearing target and the 84-megahertz clearing target.
 5 The second one that I just showed you a map to
 6 illustrate how this could be a problem is we've
 7 considered strategic bidding in a DMA only, but
 8 oftentimes there's interference across DMAs that are
 9 nearby, and so you can see here, this is two stations
 10 that are owned by the same company, by NRJ. They are
 11 in adjacent markets, and we find that if they were
 12 able to bid those in both strategically, we would
 13 actually see pretty significant effects.
 14 And so, you know, here we find, again, about 90
 15 percent payout increases from this particular larger
 16 strategic bidding area. And so I wanted to tell you
 17 this, in just putting the auction results themselves
 18 into perspective, and that's where I'll stop. The
 19 auction, as I already told you, actually ended up
 20 geolocating 84 megahertz to wireless companies. It
 21 started with a clearing target of 126.
 22 At that point, the demands in the reverse
 23 auction far exceeded the willingness to pay by
 24 wireless providers, and so there were three subsequent
 25 stages where those two were brought more into balance.

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1 The auction concluded with 10 billion in reverse
 2 auction costs, more than matched by about 20 billion
 3 of revenue that the wireless providers were willing to
 4 pay for that spectrum in the forward auction. And so
 5 at that point the auction concluded, and we're hoping
 6 that by mid-2020, all of that repurposing will have
 7 been realized.
 8 So, you know, in reconciliation, then, just to
 9 maybe remind you of our numbers, right, in our numbers
 10 we estimated that the true value to firms at the
 11 initial clearing target of 126 was not \$86 billion,
 12 but just much less than that, about five times less.
 13 And then similarly, in our simulations, we also don't
 14 find anything near the 10 billion that was finally
 15 realized at the 84-megahertz clearing target.
 16 And so in terms of why we were not able to
 17 match that at all, I wanted to remind you of these
 18 very conservative estimates that we provide by
 19 thinking about full participation and limiting
 20 strategic bidding to the MSA/DMA itself that you are
 21 in, and our results suggest that increasing those or
 22 relaxing those constraints would have given you
 23 significantly higher payouts than what we find here.
 24 What we're currently working on a little bit is
 25 trying to think about, you know, what happened after

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1 the auction. Some of our speculators did not, in
 2 fact, sell all of the stations that they had, which is
 3 one piece of evidence that we had that for them maybe
 4 this was not just flipping, and so you have sort of
 5 some numbers here.
 6 And, you know, in conclusion, I would just say,
 7 with the data at hand, it's hard for us to prove
 8 conclusively that such strategic behavior was in
 9 effect, but one thing we wanted to point out with our
 10 work, since repurposing the spectrum going forward is
 11 similarly a problem, is that market power in these
 12 auctions, to the extent that firms realize that they
 13 have it, can actually have pretty significant effects.
 14 And, you know, what we're currently then
 15 thinking about is, well, if we think about firms being
 16 differentiated, how would that change once we relax
 17 how much they can interfere with each other and,
 18 therefore, become more or less substitutable in the
 19 auction.
 20 So that's all I had. Thank you very much for
 21 your attention, and I think we have maybe like two
 22 minutes for questions, since I went over my little
 23 allotted time.
 24 AUDIENCE MEMBER: I have two questions. One,
 25 so maybe the other people here wouldn't be willing or

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<p>1 don't want to point this out, but, you know, this 2 is -- there was a campaign of buying multiple licenses 3 by a number of speculators, or however you want to 4 characterize them, in advance of this auction. You 5 know, to my mind, acquiring assets in order to 6 withdraw them or potentially withdraw them from a 7 public auction would seem to be a kind of textbook 8 violation of Section 7 of the Clayton Act. I wonder 9 if you wanted to speak to that.</p> <p>10 And then secondly, you know, I've heard a 11 lot -- I have never worked at the FCC, as you have, 12 about that forthcoming spectrum re-allocation. Is 13 there any -- do you know of any sort of initiative 14 there to treat the issues that you've brought up with 15 the last one?</p> <p>16 MS. SEIM: Let me just maybe answer the second 17 one. I don't think right now there's any efforts in 18 place to think about renewed spectrum repurposing. In 19 part, I think that is -- you know, I think the big 20 takeaway of the auction is running a complex auction 21 like this is a difficult undertaking that has taken a 22 significant amount of time. And so, you know, if you 23 think about sort of what I showed you there on the 24 slide before about reconciliation and what the 25 expected bidders might have been compared to what they</p>	<p>1 know, can all appreciate that kind of evidence, while 2 we can provide suggestive evidence from our results, 3 it's a bit hard to come by.</p> <p>4 All right, thank you very much. 5 (Applause.)</p> <p>6 MR. ROSENBAUM: Thank you very much, Katja. 7 (End of session.)</p> <p>8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25</p>
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<p>1 ended up being, demand in these markets changes pretty 2 dramatically, right, and one thing that I think has 3 happened was that over the time period that we took to 4 develop the auction, wireless demand has changed a 5 lot, and as a result, you know, that spectrum wasn't 6 as valuable anymore as it might have been when the 7 auction was initially conceived.</p> <p>8 And so I think as a result maybe of that, even 9 though I think the auction ran very efficiently and 10 obviously repurposed I think a lot of spectrum, 11 there's less appetite maybe at this current stage to 12 think about doing something like this again. And so 13 to that extent, I'm sort of unable to answer your 14 question directly.</p> <p>15 Now, as for the antitrust question, there's a 16 lot of people who have asked us that and who think we 17 should make that the hangup of the paper. We're, I 18 think, a little less willing to go there, mostly 19 because we feel that we don't have any clear evidence 20 that this was the strategy of these companies going 21 in. Flipping, per se, isn't -- I think in any mean, 22 way, shape an antitrust violation, and so to us we 23 feel like we would need to have more evidence that we 24 could clearly point to that that was something they 25 had actually wanted to pursue. And I think you, you</p>	<p>1 PANEL: ESTIMATING MARKUPS</p> <p>2 MR. ROSENBAUM: It's my pleasure to turn the 3 program over to my colleague, Devesh Raval, who will 4 be moderating a panel on estimating markups to 5 conclude the conference.</p> <p>6 MR. RAVAL: All right. Thank you all for 7 coming here. So this is a panel on estimating 8 markups, and we're privileged to have a great list of 9 panelists here to talk about this.</p> <p>10 So the first is Ariel Pakes, who needs no 11 introduction for this audience. I was going to call 12 him the father of modern empirical IO, but then John 13 Haltiwanger suggested "godfather" maybe would be an 14 alternative definition. But I want to talk about two 15 papers that he wrote about 20 years ago that are very 16 relevant to this panel.</p> <p>17 So the first is the famous BLP paper. That 18 paper was all about taking aggregate data from 19 markets, if you estimate demand, together with 20 assumptions on how firms compete, you can get markups 21 at the firm level or at the product level.</p> <p>22 Second, he also wrote a paper with J. Stephen 23 Olley about estimating production functions, and 24 that's the foundation for the supply approach for 25 estimating markups. So regardless of how you estimate</p>

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<p>1 markups, Ariel here deserves either the credit or the 2 blame, so...</p> <p>3 Second, we have John Haltiwanger. So John is a 4 macroeconomist, and usually when you mention 5 macroeconomics in an IO conference, it's a punchline 6 for a joke, but I think a lot of us don't realize that 7 macroeconomics has undergone a quiet revolution 8 towards requiring empirical evidence and especially 9 empirical evidence for microdata to support theories. 10 That's something that John has done throughout his 11 career and is really a pioneer of doing that, not just 12 with all the empirical papers, but creating the 13 underlying data sets that people now use to try to 14 take macro theories and see if they match the data or 15 not.</p> <p>16 Last we have Matt Grennan, so Matt Grennan adds 17 some youth to this panel.</p> <p>18 MR. GRENNAN: Much needed. I was wondering why 19 I was here, to keep us awake.</p> <p>20 MR. RAVAL: But I just point to you, if you 21 want to know about his work, to the presentation he 22 gave yesterday, which was about looking at price 23 discrimination in hospital markets, looking about how 24 hospitals buy different types of supplies like stints 25 or gloves, and how the markups on those can vary by</p>	<p>1 I get a -- is there a clicker for me? That's great. 2 Thank you.</p> <p>3 Okay. So I am going to be talking about, you 4 know, how do we measure markups. You know, there is 5 this very important question, which I am not going to 6 be talking on, which is figuring out why the markups 7 are there, okay? You can't tell whether they're too 8 high or too low without knowing how they got there, 9 okay? Why are we having the markups, okay? But I'm 10 not going to talk about that.</p> <p>11 So I'm going to give you an example. I'm going 12 to go through demand system stuff, production function 13 stuff, and then what you guys can requisition, okay, 14 what the FTC can requisition. So I'm going to give 15 you an example first.</p> <p>16 There was an article in the AER this year, just 17 lately, by Tom Wollman on trucks, okay? So I asked 18 Tom to take down his demand system. His demand system 19 was estimated separately from the pricing equation. 20 He had very good data on demand. He had to do this 21 because he was one of my students, so -- I wouldn't 22 have signed his thesis, but --</p> <p>23 MR. HALTIWANGER: Godfather is appropriate, 24 apparently.</p> <p>25 MR. PAKES: Maybe that's right, the wrong one,</p>
<p>106</p> <p>1 bargaining, by search costs, and by other types of 2 frictions.</p> <p>3 So the format of this panel is I'm going to ask 4 some questions, and the panelists are going to answer 5 them. So we're going to start with the first question 6 for Ariel.</p> <p>7 So I would characterize approaches to markup 8 estimations in three forms. The first is that we 9 might obtain margin data directly from firms, so 10 something the DOJ or FTC could do in a case. The 11 second is you could estimate markups using production 12 data, so that's the De Loecker method that sort of 13 motivated a recent paper saying markups have gone up a 14 lot using Compustat data. And third, through 15 estimating demand, as Ariel did in the BLP paper.</p> <p>16 So how would you assess the strengths and 17 weaknesses of these different approaches?</p> <p>18 MR. PAKES: Thanks, Davesh. Thanks for having 19 me. I've never been called a godfather before. I 20 guess there's pros -- there's good godfathers and bad 21 godfathers. I hope I'm on the good side.</p> <p>22 I actually made, just for this first question, 23 I talked to -- Davesh and I did some email 24 interchange, and I made a few slides just to describe 25 what's going on. So can we move on on the slide? Do</p>	<p>108</p> <p>1 right?</p> <p>2 So take the predicted markup down from the 3 demand system, all right, regress it on supposedly 4 exogenous variables or instruments, okay? And then go 5 to the pricing equation and regress price against the 6 characteristics of the product and wages, which was 7 the only other cost factor, and then look at the 8 coefficient of markup, which should be one if our 9 model is right, okay, and what the R2 is. That's the 10 answers, okay?</p> <p>11 It's an amazing fit, okay? If you don't put in 12 time dummies, the R2 is 0.86. The markup is within one 13 standard deviation of one. And if you put in time 14 dummies, it's 0.94, and this is directly from his 15 paper, okay? There's nothing fancy going on. It's 16 just an OLS regression, okay?</p> <p>17 So it tells you what I think is true, is that 18 it works very well in the cross-section. So I also 19 asked him to do it over time. So just look at 20 differences in price of the same good over time, okay? 21 So the characteristics are not changing over time, 22 okay? So they're not going into this regression. The 23 only thing that's going into this regression is 24 differences in competition across periods. There are 25 different competitors to these trucks every period.</p>

109	<p>1 You still get an R2 of between 0.5 and 0.6, okay, which</p> <p>2 for a behavioral equation in the social sciences, you</p> <p>3 know, if somebody is actually setting these prices, is</p> <p>4 very good. You know, labor has not seen a 0.6 R2 in a</p> <p>5 long time, okay?</p> <p>6 And, you know, I think the reason it works this</p> <p>7 way, okay, is typically we have really good data on</p> <p>8 prices, quantities, and characteristics. You know,</p> <p>9 it's just you know the quantity of cars, you know the</p> <p>10 prices of those cars, more or less, okay, and you know</p> <p>11 their characteristics. We don't need input data on</p> <p>12 cost functions to do this, okay? And, you know,</p> <p>13 really the open question is the model of pricing, is</p> <p>14 that good or bad?</p> <p>15 Actually, this is trucks, right? So it should</p> <p>16 be a durable good problem, okay, and it should not be</p> <p>17 static, but -- and I've seen this time and again.</p> <p>18 Same one when we did cars, okay? They're a durable</p> <p>19 good. It should not be a static pricing problem.</p> <p>20 But three things happen, which is markups are</p> <p>21 always smaller, at least every one I've seen in the</p> <p>22 crowded portion of the market when there's a lot of</p> <p>23 competing cars with similar characteristics. Markups</p> <p>24 are higher for high-quality or high-priced goods, and</p> <p>25 that, you know, just rationalizes the investments in</p>	111	<p>1 know, and if you're honest about productivity stuff,</p> <p>2 you know, really what you're doing is you're getting</p> <p>3 an index of sales on one side of the equation, and</p> <p>4 then you're regressing it on either an index of the</p> <p>5 cost of inputs, not the inputs themselves, or a very</p> <p>6 loose aggregate of the quantity input, like hours of,</p> <p>7 you know, very different kinds of labors, high school,</p> <p>8 university, research, the works, okay? That's what's</p> <p>9 going on.</p> <p>10 And then productivity was just the ratio of the</p> <p>11 index of outputs over the index of inputs. That's</p> <p>12 productivity. That matters for a lot of things, but</p> <p>13 it's not markups, okay? It's an index of sales over</p> <p>14 an index of inputs. It generates a lot of incentives,</p> <p>15 okay, for selection and for endogeneity, but it's not</p> <p>16 productivity. It's not markups. So now let me go to</p> <p>17 markups.</p> <p>18 So how do I get from there to markups? The</p> <p>19 first thing you need to do is separate price from</p> <p>20 quantity, okay? And so just using sales is not going</p> <p>21 to do. And the second thing we're going to need is an</p> <p>22 elasticity of output with respect to a variable input.</p> <p>23 So this is the two things that Jan needs, okay?</p> <p>24 How do we get these? We estimate a production</p> <p>25 function and assume it's Hicks neutral technological</p>
110	<p>1 getting the higher quality, okay? And markups are</p> <p>2 higher for products where a firm is marketing two</p> <p>3 products that are competing with each other, just like</p> <p>4 our theory says.</p> <p>5 So it's not exactly right. We know it's not</p> <p>6 exactly right, they are durable goods, but these kind</p> <p>7 of arguments make the estimate -- well, make the</p> <p>8 estimates make some sense, okay?</p> <p>9 On the other hand, the problem with this way of</p> <p>10 doing it, it takes a pretty detailed data set and a</p> <p>11 lot of time to do it, okay? So you're not going to be</p> <p>12 able to do it on all of the industries in the economy,</p> <p>13 okay? It's just not going to be within the feasible</p> <p>14 set, okay? And I would like to see people like the</p> <p>15 FTC doing it, but, you know, maybe to make it a little</p> <p>16 bit easier, I would have suggested having sort of a</p> <p>17 repository of data on different industries available</p> <p>18 for people. So that's markups from demand system</p> <p>19 estimation.</p> <p>20 Now I'm going to go to the production side,</p> <p>21 okay? So this is Jan and his co-authors. So let me</p> <p>22 take a step back for a second. This literature</p> <p>23 started with productivity analysis, not with</p> <p>24 estimating production functions. And if you were</p> <p>25 honest -- and I did some of this, so I'm not -- you</p>	112	<p>1 change, so the labor or the variable cost coefficient</p> <p>2 has the same proportional shift as everything else,</p> <p>3 okay? And then we assume there is an input which is</p> <p>4 purchased in a competitive market and optimized out in</p> <p>5 the short run. So you can condition on the quantity</p> <p>6 of output and the quantity of the other inputs, but</p> <p>7 conditional on those, this input is going to be</p> <p>8 optimized out in the short run.</p> <p>9 What problems do we get? So the first problem</p> <p>10 is there isn't a production function for multi-product</p> <p>11 firms, okay? It's at best a correspondence, right? I</p> <p>12 have a certain amount of inputs. I can transfer them</p> <p>13 into different amounts of -- different kinds of</p> <p>14 output. It just doesn't exist, okay?</p> <p>15 So this is often, you know, also true at a</p> <p>16 plant level, because I've looked at plant-level data,</p> <p>17 okay? That was surprising to me when I looked at it,</p> <p>18 okay, but it is true, okay? And even if you did have</p> <p>19 plant-level data, okay, you know, the firm is not</p> <p>20 optimizing inputs for the plant. It's optimizing</p> <p>21 input for the multi-plant firm. And that's a</p> <p>22 different question with a different answer. Is that</p> <p>23 clear? So it's problematic, okay?</p> <p>24 The other kinds of things that are problematic</p> <p>25 about it is you really need, you know, the right --</p>

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1 you need to have an index of inputs that's correct in
2 some sense. What is capital, okay? And I need to
3 measure them right. So, you know, you need to
4 aggregate capital stock, and you're averaging things
5 that were bought at very different times, okay, and
6 used for very different things, okay, and aggregate
7 labor stock, okay?

8 Technological change has to be Hicks neutral,
9 and then, you know, the same problems that arise in
10 productivity analysis, selection and endogeneity have
11 to be dealt with, okay?

12 Now, there is this huge advantage, okay? So
13 those are the problems, and they're substantial, okay?
14 There's this huge advantage that you can do it for
15 lots of firms, lots of time, okay? It's quick, at
16 least relative to the demand system stuff, okay? If
17 you go to the LRD or whatever other data set you -- I
18 wouldn't go to the Compustat, but LRD I would go to,
19 okay?

20 And, you know, you can give them the type of
21 data you have. If you believe your, say, materials
22 input is optimized in the short run, you really
23 believe single-product firms is enough, you don't
24 worry about the selection problem, and, you know,
25 there's a reason that there's multi-product firms.

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1 It's not a random draw of firms, okay? If you believe
2 all that, you can do it very quickly. And you can't
3 do that with the demand side. You couldn't do it for
4 the whole -- you just -- it's just not in the cards,
5 okay?

6 So the third thing is obtaining margin data
7 directly from the firms. So I have less experience
8 with this. The first two I've worked on, okay? This
9 one I've never worked on. The first question is what
10 do you ask them, I think, either for -- and you would
11 ask them different things depending on what you want.

12 If you were just doing merger analysis sort of
13 conditional on synergies, that's one thing. If you
14 were trying to look at synergies, okay, which they're
15 going to claim when they walk into the FTC or the DOJ,
16 right -- we're not going to do this to raise price,
17 we're going to do this because we have cost synergies,
18 okay -- you're going to be looking at very different
19 things, okay?

20 If you want marginal costs, you want the
21 inputs -- you need the inputs which contribute to that
22 marginal cost. There's an issue -- there becomes an
23 issue of inputs like marketing that were in the
24 question, because, you know, they do -- they are
25 marginal in some sense, okay, but the returns come

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1 over time, so I need a depreciation rate of something
2 like that to do this, okay?

3 And when you're evaluating synergies, the
4 arguments -- you're looking more at fixed costs and
5 things like that. So I just looked at the bank data
6 entry, and one of the big things that happens when
7 banks enter is they close branches. When they do
8 mergers, they close branches. That's one of the
9 reasons they're doing it, okay?

10 So is that -- you know, is that a marginal
11 cost? Is that a savings? It's a savings in cost. At
12 least it's a synergy of some form, okay? On the other
13 hand, it's not very good for consumers sometimes. You
14 might want to take that into consideration. So
15 there's a lot of issues in that, in what to ask for
16 and how to use it.

17 And then there's also always the question of,
18 you know, when you ask for it, what are they going to
19 tell you, okay? So there's an incentive compatibility
20 problem a la Maskin and Tirole, okay, or Laffont and
21 Tirole. It's a little bit mitigated, I've got to
22 admit, if you ask questions -- you find out margins
23 before the issue that is currently arising is
24 happening with the firm. So if you have emails from
25 prior -- from two years before this when they weren't

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1 thinking of the merger and somebody was telling you
2 something about marginal cost, okay, that would be a
3 different way of looking at it.

4 So I've told you all the problems, but that's
5 my role as an academic.

6 MR. RAVAL: So do either of you want to
7 comment?

8 MR. HALTIWANGER: Sure. It's a little hard to
9 follow the godfather, particularly on this topic, but
10 let me -- one, I'll say I agree with everything Ariel
11 said, and hopefully what I'm about to say isn't just
12 piling on, but I also have some questions, maybe
13 particularly for both panelists, given at least one
14 alternative that I think Ariel didn't mention and has
15 become popular in the recent literature.

16 So let's talk a little bit more about
17 De Loecker Eeckhout. So just as a reminder, you know,
18 kind of the key equation that they use to identify the
19 markup is very simple, right? The markup is the ratio
20 of the estimated factor elasticity for a variable
21 factor of production, like materials or of labor if
22 you decided labor is a variable factor of production,
23 to the cost share of that factor of revenue.

24 And the good news is we've got lots of good
25 data on cost shares of revenue, so that's sort of the

117	<p>1 easy part, but as Ariel has pointed out, we don't 2 actually have, and not off the shelf, we have to work 3 really hard to get that factor elasticity. With all 4 due respect to the De Loecker Eeckhout paper, I don't 5 think they actually have factor elasticity estimates 6 for all the reasons Ariel has talked about, but a key 7 one is that at least that paper does not have the P 8 and the Q data that you need to be able to separate 9 all this out.</p> <p>10 I think there's another issue that I think we 11 also -- once you just sort of stare at that formula 12 for a bit, that makes you think, well, wait a second, 13 why do I want to put all the heterogeneity on the 14 markup side? Why don't I want to put equally as much 15 heterogeneity on the technology side, because in 16 principle, that factor elasticity might actually vary 17 both across firms and time?</p> <p>18 So what do we typically do? We end up using 19 the proxy methods, which very much started with Olley/ 20 Pakes, and those methods are somewhat data hungry, and 21 so we often -- to get these, we pool across plants and 22 time, so to get time and variant kind of measures.</p> <p>23 So it is kind of piling on. It's all the 24 things that Ariel talked about, but I think on top of 25 that, I think we ought to be thinking about</p>	119	<p>1 integrated on a regular basis. So it's actually kind 2 of phenomenal, that kind of data. It's kind of 3 economic census every year in that respect.</p> <p>4 So again, I think there's hope. There's a 5 variety of European countries that also have this 6 data. So I think we can start going after some of the 7 kinds of issues that Ariel talked about.</p> <p>8 And the last thing I wanted to say here is 9 there's a method that's become I'd say increasingly 10 popular, at least in terms of a paper that's getting 11 published in prominent places, and also I'd say the 12 macro literature often uses the estimates of markups 13 or essentially the elasticities of substitution from 14 this literature, and it's really more out of -- it 15 emerged out of the trade literature, and the most 16 recent sets of papers are the papers, for example, the 17 paper by Hottman, Redding and Weinstein, in the QJE.</p> <p>18 So that's a paper, just if you're not familiar 19 with it, uses -- you know, what's become increasingly 20 available is transactions-level data, literally UPC 21 code-level data at the P and the Q level. And what do 22 they do? They write down at the product level a 23 pretty simple model basically of demand and supply, 24 but it's at the product level, by the way, so they 25 overcome some of the issues that Ariel was talking</p>
118	<p>1 heterogeneity in technology as much as heterogeneity 2 in markups. And so when I look at that paper, there's 3 something going on, clearly, with the cost shares of 4 variable inputs in terms of revenue, but I don't know 5 whether it's the markup or it's changing technology.</p> <p>6 So a somewhat more optimistic view, it is true 7 that there are data sets, even in the United States -- 8 although less in the United States than in other 9 countries -- where we do actually have the P and the Q 10 data. So at least for a limited number of products in 11 the United States -- and this is work I've done with 12 Chad Syverson, but Chad has done it for a whole 13 variety of papers -- there is P and Q data for a 14 limited set of products. And for some remarks I'm 15 going to make later about what's going on in macro, I 16 think we've learned some things out of that kind of 17 work. So there's some hope.</p> <p>18 Actually, in other countries, one country I'm 19 working actively with their data is I'm working with 20 Marcela Eslava in Colombia. Nicely, you know, unlike 21 the United States, it's not a Balkanized statistical 22 system, so, indeed, basically the price program is 23 fully integrated with the annual survey of 24 manufacturers. So they actually have detailed P and Q 25 data, not only for outputs, but materials, all</p>	120	<p>1 about already.</p> <p>2 And then there's huge identification problems, 3 right? Because the question is, I've got -- if I 4 could write down -- by the way, these are a nested CES 5 environment, to do this. They've got to overcome the 6 problem that cost shocks are going to be correlated 7 with the demand shocks. And so what are they going to 8 do? And they don't have the instruments that all 9 these very careful industry studies do.</p> <p>10 So they do what Rob Feenstra suggested way back 11 in '94, but perhaps it's more palatable in this data. 12 Why is it more palatable? Because basically they 13 double-difference their equations, and basically they 14 sweep out firm by time effects. And you could -- they 15 argue that they're sweeping out lots of things, and 16 then they say, okay, well the double-difference 17 shocks, they make the assumption -- a pretty strong 18 identifying assumption -- that they're uncorrelated, 19 and that gives them a moment condition, and then they 20 go and they estimate the elasticities.</p> <p>21 Now, again, we're often looking for things you 22 can do at scale. They do this at scale, okay? So 23 they take the -- for example, the Kilts data from the 24 Chicago Booth and they've estimated it over 100 25 markups relatively quickly across a wide variety of</p>

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1 product groups, and they've even estimated it at --
2 some of their estimates are more at the product
3 modular level, so over a thousand markups. So I think
4 that's another horse in the race.

5 And last issue that I guess I've been struck by
6 is that Hottman, Redding, and Weinstein have argued
7 that this method, in principle -- let's suppose they
8 really did get the elasticities of substitution
9 correctly estimated here. This enables them to
10 extract basically from the demand equation the
11 variation in quality across products, at the product
12 item level.

13 So, in turn -- and it's also the case that this
14 data has lots of entry and exit of products, so -- and
15 this was one of the -- those who know the Feenstra
16 work, one of the original insights of Feenstra was a
17 way to adjust standard price indices for new product
18 variety.

19 So why do I bring this up? Because they've
20 developed a method -- and this is more in the more
21 recent papers, the Redding and Weinstein papers -- a
22 method for price indices that adjust for quality
23 change both from product variety and actually for
24 common goods.

25 And I find it interesting -- and, again, it

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1 would be nice to hear I'll say especially from the
2 godfather about this -- is, you know, the methods that
3 Ariel is applying here very much are tied to the
4 hedonic literature in many respects, and that's one
5 way -- and I think a very powerful way -- to adjust
6 for quality.

7 This offers an alternative. I don't think we
8 fully understand how they compare to each other, but
9 it's kind of interesting that these alternatives --
10 both these two alternatives yield estimates of markups
11 and estimates of quality change, I think two things we
12 care a lot about.

13 MR. GRENNAN: It's hard to add. It's a pretty
14 comprehensive set of comments being made here. I
15 guess maybe just two things that are a little bit
16 particular to -- I think I was asked to jump in here
17 because I have a bit of experience trying to apply
18 these method to product markets like medical devices
19 and pharmaceuticals, where the markups tend to be
20 quite large, or at least markups over marginal cost of
21 the actual good, the marginal cost meaning, like, the
22 marginal cost of production and distribution, say, of
23 this actual good tend to be quite large. And I think
24 at least in those types of markets, it tends to be --
25 you know, estimating this sort of elasticity of an

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1 output with respect to an input is likely to be quite
2 small and noisy. So I think it's kind of -- it's a
3 very challenging to imagine that approach applying I
4 think to this set of markets.

5 In terms of estimating demand and doing it at
6 scale, you know, the paper I presented yesterday is an
7 example where we're trying to do something not quite
8 at the scale of some of the articles that John was
9 citing, but, you know, across quite a wide variety of
10 medical inputs, and there we're doing something that
11 actually conceptually is not entirely different from
12 he was talking about, right?

13 We're using nested logit instead of nested CES
14 models, right, but hoping that this is kind of -- this
15 plus lots of panel data that allow us for a lot of
16 rich fixed effects is going to capture a lot of kind
17 of first order things that we're interested in in the
18 data. You know, we add -- very particular to our
19 context, we have some instruments to add to it.

20 But I think, you know, anecdotally, I don't
21 have a quantitative sense of this, but my kind of
22 qualitative impression is that if you aggregate it
23 over a lot of very, very careful IO studies in
24 particular industries, once you have enough data to
25 have very, very fine-grained fixed effects, a lot of

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1 times, you know, adding the instruments don't make a
2 huge difference. So there might be something to be
3 said for this type of approach and its scalability.

4 And I guess I would add to that that, I mean,
5 to me, all of my work is always in -- and most of our
6 work, right -- is in thinking about particular policy
7 questions, right? So this what's underlying the
8 markup, Ariel, you know, decided not to address it,
9 but really that's usually what we'd would want to
10 know.

11 And so to, you know, to actually address most
12 of the policy questions we're interested in, you know,
13 if you don't have some sort of model of demand, it's
14 very difficult to start to address those questions.
15 So I think that's why you see many of us skewing
16 towards that in our work as well.

17 MR. RAVAL: Does anyone want to add?

18 MR. PAKES: Just a couple quickly.

19 On the linear fixed effects, when you have
20 stuff going in and out, it's not linear anymore.
21 There's a selection problem, and it's problematic.
22 It's correlated with things. So that's true.

23 You know, this literature on estimating
24 production functions starts with this article by
25 Mundlak about agriculture, you know where the fixed

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1 effect was the quality of land, and it didn't change
2 too much over time, but, you know, farms weren't going
3 in and out.

4 In this case, the products are leaving because
5 they're being obsoleted by better products, and it has
6 an effect on the analysis. On the hedonic stuff, you
7 know, fundamentally, the characteristics base is just
8 an approximation, right? There really isn't a
9 quantity out there. We don't have all the right
10 characteristics to put in the error term.

11 So if you did it, you know, the other way --
12 and you could actually do it, you know, we thought you
13 couldn't do it -- so 200 cars with 200 prices for each
14 one is, what, 40,000 cost price elasticity? There's
15 no data set that's ever going to estimate that many
16 cost price elasticities. That's why we went to
17 characteristics. But if you can do it, you know, it's
18 great, but you still need the production function.
19 You still need --

20 MR. RAVAL: I agree with that.

21 MR. PAKES: -- and that's where I think most of
22 the problems lie. That's where we don't really have a
23 good grasp on it.

24 MR. RAVAL: So the second question, and this
25 was brought up I think by both John and Matt, but it's

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1 to John. So I think there's a lot of demand for
2 macroeconomics for an aggregate markup. So the first
3 question is, what role do you think researchers in IO
4 should have in examining this question?

5 So one way you could think about doing that is
6 just aggregating from estimates from individual
7 industries. So maybe Nate Miller in the audience
8 knows about beer and cement, and Kate Ho knows about
9 insurance companies and hospitals, and Ariel can make
10 his students work on the industries we don't know
11 about, and eventually we get to an aggregate markup.

12 Another approach would be to do cross-industry
13 studies, which IO has largely abandoned and has been
14 starting to be done by macro and trade people. So
15 what do you think about that?

16 MR. HALTIWANGER: So there is enormous interest
17 in macro, if you're not aware, in what's going on with
18 the evolution of markups. And I think it's fair to
19 say -- and Ariel has already basically touched upon
20 this -- that for macroeconomists, if we're going to do
21 this, we need to use one of these methods at scale,
22 all right? We're going to need to be able to do this.
23 That's not to say that we shouldn't be learning from
24 the insights from the microeconometrics about both the
25 issues and literally the methods in order to be -- in

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1 order to get there.

2 So let me try not to -- you know, I'm watching
3 the clock here. I could go on for a while about how
4 macroeconomists are using markups, but let me try to
5 talk a little bit about and use De Loecker Eeckhout
6 actually as both sort of a source, why we're so
7 interested, and then various ways of thinking about
8 things.

9 So remember De Loecker Eeckhout, the stuff that
10 showed up in the New York Times for De Loecker
11 Eeckhout was about the aggregate markup, right? But
12 actually really what that is, those of you who read
13 the paper, of course, that's the activity-weighted
14 first moment of their distribution of markups. And
15 actually their paper is very much as much about what
16 the "aggregate" markup, the first moment is doing, as
17 they -- they have quite interesting things to say
18 about the evolution of the distribution, changing
19 dispersion, skewness, the connection between changing
20 skewness, and the first moment, and so on.

21 So, again, I think -- and I'll say just
22 enormous interest in that, and, indeed, you know,
23 where this has sort of led, there has become great
24 interest, partly from De Loecker Eeckhout, that if we
25 took -- the one possibility is that competition has

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1 become more imperfect in the United States over time.
2 We are a less competitive economy, which is, you know,
3 a controversial statement, and this is related to the
4 question about, where are these markups from and what
5 might be driving them?

6 Now, there's a parallel literature that's
7 emerged in macroeconomics that I'm almost hesitant to
8 bring up in this audience, because actually there was
9 a Jackson Hole conference just recently very much
10 about this, and it was very much focused on changing
11 concentration, and there are lots of macroeconomists
12 who have been using industry-level concentration
13 measures to shed some light on this.

14 Two of the people at that conference were from
15 the IO community, particularly -- and probably more
16 than that, maybe I'm forgetting others -- but Chad
17 Syverson was there and so was Carl Shapiro, and both
18 of them -- I think Chad called using kind of
19 concentration metrics and said -- one of them called
20 it the original sin and the other one called it the
21 forbidden regression. I don't know which one.

22 So both of them -- so basically they said you
23 have to be incredibly careful about using this outcome
24 variable and they came through examples. You don't
25 know which direction -- even as Chad walked through

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1 examples, concentration may go up or down with the
2 changes in competition depending upon the model and
3 the structure. So I mention that not to advocate for
4 the use of concentration, particularly in this
5 audience, but rather just to indicate the enormous
6 interest.

7 I wanted to build on a little bit back again to
8 De Loecker Eeckhout, that they're really much more
9 than about first moments, they're about the
10 distribution of markups, and I wanted to talk briefly
11 about why macroeconomists are so interested in the
12 evolution of the distribution of markups, what they
13 are, how they might vary across time, countries,
14 industries, and the like.

15 And also I think we've learned something from
16 the literature -- I'm just about to talk about it --
17 that provides indirect evidence about what might be
18 going on with markups. So what literature am I
19 referring to? So one of the areas that's become a
20 focus I'd say in the last -- particularly the last
21 decade, although it's an older topic than that -- is
22 misallocation. So what's the -- it's become kind of a
23 working hypothesis that especially if we're trying to
24 explain differences in economic performance across
25 countries, but often also within countries over time,

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1 that deteriorations in aggregate productivity reflect
2 changes in misallocation.

3 And the paper that's probably gotten the most
4 attention, certainly the most cites, I think, is a
5 very nice paper by Hsieh Klenow, and I want to talk
6 very briefly about the Hsieh Klenow paper, both
7 because of its insights, but also then I'm going to
8 come back and talk to you about what might be going on
9 in the data that we've been looking at that actually
10 might be driven exactly by the De Loecker Eeckhout
11 changes in markups.

12 So here's sort of the Hsieh Klenow 101 for
13 those of you who are not familiar, really quickly. So
14 like most macroeconomists, they write down a very
15 simple model of the production technology and the
16 demand structure. So critically they use CES
17 preferences and end up actually, even though they --
18 on the production side, by the way, they allow for
19 heterogeneity in production elasticities, which they
20 measure from cost shares, by the way, like growth
21 accounting. On the demand side, they take one number.
22 The elasticity of substitution is four, okay, and so
23 the markup is 1.33 in their very simple calibration.

24 So here's the key insight, by the way, and it's
25 a very powerful insight -- and in some ways too

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1 powerful as I'm going to argue in just a second -- but
2 nevertheless, I think it's very insightful, including
3 for this discussion about the evolution of markups.

4 So if you write down a -- write down this model
5 and you think about the -- what we'll call the
6 frictionless benchmark. What's the frictionless
7 benchmark? Where marginal revenue products are all
8 equalized. Well, you could say -- we've actually
9 known about this for a long time, but they really
10 emphasize this. If marginal revenue products are
11 equalized in exactly this setting, but inside
12 industries, measures of revenue dispersion, exactly
13 the measures that Ariel was just talking about, the
14 sales per unit input should exhibit no dispersion.
15 It's a consequence of margin revenue products being
16 equalized.

17 But as Ariel and I know -- we've been doing
18 this for a while -- there's enormous dispersion across
19 businesses in these measures, and not only that, in
20 the classic Olley/Pakes paper, it wasn't just that
21 they did great things in terms of estimating the
22 production or sales function, but they showed that as
23 the telecommunications equipment industry underwent
24 changes in the economic environment, there were
25 important changes in measures of allocated

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1 efficiencies. So these measures are quite indicative.
2 So the question is, how do we reconcile the Hsieh
3 Klenow view with I'll say maybe the Olley/Pakes view
4 of TFPR dispersion?

5 So, remember, let me just go -- I didn't quite
6 finish the punchline of Hsieh Klenow. So what did
7 they do? They say, well, look, we see enormous
8 dispersion in revenue productivity dispersion across
9 firms and plants in the same industry. It must be
10 driven by wedges, some sort of distortion.

11 And so they found, for example, that revenue
12 productivity dispersion is much larger in China and
13 India than the United States, and they -- given their
14 strong assumptions, they could literally back out the
15 distribution of wedges, and then they could actually
16 do a calculation that said, here's all the allocated
17 inefficiency in China and India that resulted.

18 Now, as we thought further about this, we
19 realized there's a whole host of things that might be
20 driving revenue productivity dispersion above and
21 beyond the kind of wedges and distortions that they're
22 talking about. Some of them are things like
23 adjustment costs, and you say, well, gee, how do I
24 distinguish between an adjustment cost and a
25 distortion? Well, lots of us have been certainly

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1 writing down models, dynamic models where even a
2 social planner faces a certain amount of adjustment
3 frictions for labor or adjusting the scale, and I know
4 there's lots of interesting things in the IO
5 literature about this. So one tension in the
6 literature is how to back out all the -- I'll call it
7 the wedges and frictions that are part of the
8 environment versus the residual wedges that are
9 present.

10 So now let me get back to the distribution of
11 markups. So I mentioned that there are at least some
12 products in the United States for which we have the P
13 and the Q data, and there's lots of data sets around
14 the world, I mentioned Colombia, but there's data sets
15 in Europe and so on. And not that we've solved of
16 Ariel's problems, but -- when we do this, but when we
17 do this, we can't -- we have a lot at least at being
18 to estimate the production technology, all right?

19 And so because why? Because we can -- we can
20 compute a measure of Q. We still have multi-plant
21 firm -- multi-plant -- excuse me, multi-product plant
22 issues to confront, and actually, recently in my work
23 with Marcela Eslava, we've been going after just that
24 as well, but I don't want to go down that path right
25 now.

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1 But here's one of the things that we have
2 found, and this is particularly in my work with Chad
3 Syverson and Lucia Foster. So one is the measure of
4 TFPR, and I've already told you that TFPR, in
5 principle, may, under the Hsieh Klenow assumptions,
6 only reflect wedges. But we've found when we've used
7 the P and the Q data, that the underlying -- I'm going
8 to call it TFPQ, the underlying productivity -- and by
9 the way, that measure really may be more -- a better
10 way to think of it is a competent measure of both
11 productivity and demand or quality, but let's just
12 call it TFPQ for right now.

13 We found an incredibly high correlation between
14 TFPQ and TFPR. I think that correlation is really
15 important because it actually helps explain why Olley/
16 Pakes found some of the findings they did; that,
17 indeed, the TFPR measure that they were essentially
18 using is highly correlated with the TFPQ measure, and
19 that's why the Olley/Pakes -- amongst this group,
20 probably the proxy method is the most famous, but
21 their very simple and very nice decompositional
22 allocative efficiency was also a very powerful result
23 in that paper, and I think it's partly being driven by
24 the fact that we find such high correlation between
25 TFPQ and TFPR.

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1 So the question is, why is there such a high
2 correlation between TFPQ and TFPR? And I am going to
3 bring this to a close and bring it back to markups.
4 So one possibility, if I -- is that it's correlated
5 distortions, right? I've got wedges out there, and
6 there's some black box reason. That might be. I
7 think there's probably some of that, but I actually
8 think that we have much better explanations of this
9 correlation.

10 So one of them is actually something I've
11 already mentioned, is adjustment costs. As soon as
12 you write down an adjustment cost model, then it's
13 going to be the case that as a firm gets hit by a
14 shock, it's not going to adjust completely, it's going
15 to take time, and as a result, even in the CES
16 framework, you know, what's driving this Hsieh Klenow
17 result is there's actually a negative unit elasticity
18 between P and TFPQ, and that's going to disappear in
19 an adjustment cost model.

20 But what's another powerful explanation that I
21 think actually may be playing a huge role is variable
22 markups and, indeed, markups that increase with TFPQ.
23 Do we think there's evidence of that? Yeah, actually,
24 there's a very nice paper -- it's actually more of a
25 theory paper, but I was really struck by its

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1 discussion on the evidence, this paper by Dhingra and
2 Morrow coming out in the JPE about variable elasticity
3 models. And it's actually much more about how to
4 think about entry/exit models with variable
5 elasticity.

6 But it partly, in its motivating section, it
7 talked a lot about what they regarded as the indirect
8 evidence that markups are variable across firms, and
9 actually tend to be increasing in size and
10 fundamentals. And basically what they cited over and
11 over again was the incomplete pass-through literature.
12 There's lots of literature that suggests that
13 businesses, when they get hit by costs, do not pass
14 those costs on completely.

15 One good way of explaining that is, indeed,
16 variable markups. So now I've come full circle. So I
17 think macroeconomics cares a lot about, not
18 surprisingly, the misallocation. To be able to
19 measure misallocation, actually we need to understand
20 the shock process that's hitting businesses. We need
21 to understand the heterogeneity and the technology.
22 We need to understand the heterogeneity and markups to
23 be able to get at all these kinds of things.

24 And so guidance from the IO literature -- so
25 back again to your original question -- are the

137	<p>1 macroeconomists hungry for good estimates of the 2 distribution of markups and how to think about this? 3 You betcha. And not only that, tell us about the 4 distribution of markups, but also how they vary with 5 key fundamentals like TFPQ. And I'll stop. 6 MR. RAVAL: Do either of you want to comment? 7 MR. PAKES: Just one quick comment on the 8 Olley/Pakes stuff. 9 So it may well be true what you've said, that 10 correlation with TFPQ, but there, if you look at 11 Olley/Pakes, look at the mean -- the average 12 productivity as you go along. The distributional 13 stuff that John said is correct, but the mean actually 14 doesn't increase, and this is probably the fastest 15 moving -- it's telecommunication equipment. Stuff was 16 moving very fast. There was a lot of technological 17 change. 18 And I think the reason for it is price was 19 going down, because they opened up the market and 20 there was competition. So, I mean, it's got to -- it 21 depends on the question you're asking, what was going 22 on, okay? So just that. 23 MR. RAVAL: All right. So the next question is 24 for Matt Grennan. 25 So some of the industries we study, such as</p>	139	<p>1 from markups relative to the marginal cost of 2 production and distribution of a good is important, 3 right, because they're very conceptually distinct in 4 terms of, you know, what they tell us about 5 implications for short- and long-run efficiency and 6 responses to various changes in policy or in the 7 economy. 8 I'll give -- maybe two examples might be 9 helpful, right? So in hospital markets or medical 10 markets, right, having a good sales force for, say, 11 selling a pharmaceutical or a medical device seems to 12 be an important thing for selling a lot of the 13 product, right, for generating sales in those markets, 14 and probably part of this is that there's some 15 value-added service component sometimes. 16 In medical devices, it's part of just how 17 distribution works. You know, there might be part 18 informative aspects to this, right? You're getting 19 the word out about these technologist and how they're 20 best used and so on. And, you know, there's likely in 21 many cases also persuasion in these activities, right? 22 And if you have, you know, an oligopoly or a 23 monopoly industry, as we often do in some of these, 24 you know, there's likely maybe some business-stealing 25 aspects to those. And so in that case, it may be very</p>
138	<p>1 pharma or high-tech, are characterized by a high fixed 2 cost and low marginal cost. So is a markup over 3 marginal cost even relevant for these industries, 4 first of all? And second of all, you know, one way to 5 view the De Loecker Eeckhout evidence is maybe the 6 relevant points of fixed cost versus marginal cost is 7 changing. And so if you start moving towards a more 8 high-fixed cost technology, that could lead to 9 increases in measured markups. 10 So do you think that's what's going on, and 11 what should we be doing about it? 12 MR. GRENNAN: Yeah. So I think this question 13 of, you know, the role of fixed costs, so I think -- 14 you know, at least when I hear that, I think, you 15 know, costs of research and development or maybe costs 16 of adopting new, expensive technologies, or at least 17 kind of quasi fixed costs, like kind of sales, 18 marketing or management, you know, and are those 19 leading to some rise in markups. 20 I mean, I'm not sure that we have great 21 evidence. I think it's a very interesting hypothesis 22 that we should probably all be exploring to some 23 degree, but, you know, in terms of -- so I'm not sure 24 I can answer, you know, are those at the root of 25 things, but I do think that keeping those separate</p>	140	<p>1 inefficient, this spending, right, and maybe even if 2 you're persuading people to allocate things to the 3 wrong patient during the wrong circumstances, perhaps 4 even value-destroying, right? So, you know, I think 5 you'd want to keep those things separate when you're 6 thinking about markups in that case. 7 The other might be, you know, in these 8 industries, as in a lot of intermediate good 9 industries, the prices that you're looking at are 10 often negotiated, right? So this markup not only has 11 something to do with, say, demand elasticities, 12 competition, and marginal costs, but also where some 13 bargaining parameters tell you that the price is 14 ending up in between some bounds that are created by 15 those other forces, right? 16 And if you think about -- you know, look at any 17 of the estimates that we've been getting from these 18 sort of models, there tends to be a lot of variation 19 left in this bargaining residual that's kind of 20 explaining where prices are ending up, right? And 21 kind of qualitative evidence in my experience suggests 22 that, you know, what's driving these? A lot of things 23 like managerial skill, effort, maybe information, and, 24 you know, if this is just transfers, then investment 25 in this kind of bargaining, you know, effort is just</p>

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1 pure social waste, right?

2 If it's not transfers, then this affects

3 allocations either in the immediate market, because

4 you can't contract on quantity, or in downstream

5 markets because this ends up being an input cost for

6 those downstream markets. Then, you know, investment

7 in negotiating a better price by suppliers is

8 unambiguously I think a bad thing, typically. I mean,

9 there's caveats for oligopolies, and if we're aligning

10 prices with marginal costs and so on, but probably

11 likely a bad thing.

12 But on the buyer side, investment in

13 negotiating better price is probably also conversely

14 unambiguously good, because you're driving prices

15 closer to cost potentially and increasing at least

16 short-run allocative efficiency in that sense.

17 So I think that, you know, the big takeaway to

18 sort of answer the question, yes, I think the

19 markups -- the traditional markups are still very

20 valuable in these cases, and I think that these fixed

21 or quasi fixed costs, you know, we should be thinking

22 about them, but we should be thinking about them I

23 think as distinct components in how they interact with

24 these markups.

25 MR. RAVAL: Do either of you want to comment?

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1 MR. PAKES: I actually -- my only comment --

2 maybe two things. We're not -- there's a sense in

3 which we're not thinking about dynamics, and, you

4 know, in certain industries, that's where -- if you

5 were doing a merger in pharmaceuticals, that's the

6 first thing I would worry about. I would worry about

7 the R&D policy of the industries.

8 I thought of that mostly because of what you

9 said about the bargaining thing. You know, in the

10 hospital thing, which you've worked on, the thing that

11 I think is most interesting about the bargaining thing

12 is it splits the profits, and it's going to determine

13 investment incentives. Depending on where it splits

14 the profits, we're going to see, you know, arms races

15 or we are going to see savings in costs, and we're not

16 focused on that, and I think we should be focused on

17 that. I'll just leave it there.

18 And, you know, the reason we're not focused is

19 it's difficult, but, you know, we can start with

20 something, like reduced-form stuff, anything, to get a

21 handle on what's really going on with the investment

22 stuff, so...

23 MR. RAVAL: So the next question is for John.

24 So, as many of you know, the FTC has 6(b)

25 authority to subpoena firms, and we used to ask firms

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1 for data on profits, revenue, and other variables by

2 line of business, but we haven't done that since the

3 1970s. So is there data that companies have that is

4 not already collected by the Census or someone else

5 that would be useful for markup estimation, for

6 understanding competitive conditions? And if so, what

7 would be useful and should we try to do that?

8 MR. HALTIWANGER: So a really good question.

9 By the way, it's very difficult to say we don't need

10 more data, but let me talk about I think where we

11 stand relative to when the line of business data were

12 collected.

13 So actually I went back and looked at a very

14 nice paper written and published in 19 -- I think it

15 was 1991, by Ravenscraft and Wagner, and it talked

16 about the value of the line of business data, and

17 actually it compared it to at that time, what was

18 considered a new entrant in the market, the LRD, but

19 it also compared it to Compustat and so on.

20 So here's the good news. Let me try to give

21 you a little bit of a sense of I'll say the enormous

22 progress the Census Bureau has made, in particular, in

23 building business-level data sets. So the LRD, the

24 one that, you know, Ariel and I started working with a

25 very long time ago is manufacturing only. It's built

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1 on the Annual Survey of Manufacturers and the Census

2 of Manufacturers.

3 It had reasonably good establishment-level

4 identifiers, and kind of okay firm-level identifiers.

5 So you could do some analysis, but we didn't really

6 have, even though underlying this there was a Census

7 Business Register, we really had not built a

8 longitudinal version of the Census Business Register.

9 That now exists. It's called the LBD, and you could

10 say we're not very creative about coming up with new

11 acronyms. It's the Longitudinal Business Database.

12 It's a remarkable database. It's from

13 administrative data, and it tracks -- and survey data,

14 I should say, because -- you'll see why in a second.

15 It actually tracks every establishment in the private

16 sector over time, and it has all the parent linkages.

17 And where is that all coming from? The parent

18 linkages are coming from the economic censuses and the

19 Company Organization Survey.

20 And so you can do a remarkable amount about

21 firm versus establishment dynamics. Now, currently,

22 that data set -- this is going to eventually get back

23 to your question -- that data set, one of the primary

24 variables -- I don't know, we've got incredibly good

25 location data, we've got the organizational structure

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1 data that we just talked about. In terms of sort of
2 the economic outcome variables, the key variables that
3 are available are employment, payroll, and revenue.
4 The employment and payroll data come from payroll tax
5 reports, and the revenue data comes from business tax
6 returns.

7 Now that data, it turns out, Census is getting
8 the complete dump of all forms of business tax
9 returns. So there's lots of information on costs of
10 materials, actually other kinds of costs. There's
11 even -- you can certainly -- you can build an
12 accounting profits measure from the administrative
13 law. So in that sense, the data are sitting there,
14 and you need folks to kind of come and invest and
15 spend time building that up.

16 And you say, well, how hard can that be? So
17 the LBD is something that was created in the last
18 decade or so, and then just a few years ago, you know,
19 one of my research assistants and now co-authors,
20 Robert Kulick, we had him add the revenue data. It
21 took him three years to add the revenue data, to be
22 able to sort through -- he had to understand all the
23 different tax forms and the fact that Census was
24 changing the way they were doing things over time and
25 so on.

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1 But anyway, the point here is I think we are in
2 much better shape than we were back in 1991 when
3 Ravenscraft and Wagner wrote their paper on I'm going
4 to call it the core accounting profits notions, the
5 notion that there's -- and to be able to do things at
6 both the establishment and the firm level. And I'll
7 say as well, because of that -- and there has not been
8 enough of this done as well -- but an enormous amount
9 can be done on studying merger activity and changes in
10 ownership structure. The data are there. People were
11 beginning to push the data hard in that direction.

12 Now, what do I think is really missing? And my
13 question is, you know -- so I don't think we are
14 missing the kind of line of business notion is the
15 point. I think we're doing a pretty good job, and I'm
16 going to go ahead and emphasize it. The industry
17 codes are fantastic, okay? They're state of the art
18 industry codes. Why? Because they come out of the
19 economic censuses, where you really ask the detailed
20 questions. So that enables you to track business
21 activity.

22 So what are we missing? Well, we could do a
23 lot better on capital if we possibly could. So
24 capital is a really hard one. Ariel sort of talked
25 about this. So lots of, you know, basically measures

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1 of -- there are some measures in the accounting data
2 on capital expenditures, and there's book values and
3 so on, but it's pretty crude. So helping just figure
4 out what's going on with capital, it would be a big
5 deal.

6 The other one we've already hinted at, what do
7 I think we're really missing in the United States, and
8 the question is whether, you know, there are gains
9 from trade here somehow or another, is P and Q data.
10 That's where we're really in deep water. The set of
11 products at Census at least for which you can do P and
12 Q is, you know, I think we -- we've done interesting
13 studies, but I was talking earlier about going to
14 scale to be able to look at various things. Can you
15 go to scale -- go at scale? No, it's only 150 limited
16 products in Census where you have the ability -- and
17 it's only every five years anyway -- to do P and Q.

18 Another place we don't have much good data --
19 and I don't have any idea whether your data would --
20 data you could get ahold of or what folks in this room
21 work with -- but we know very little about the supply
22 chain. So we don't know who buys from whom, and so
23 even some of the recent work that, for example, Chad
24 has done with Olley is work that was in -- you know,
25 they started getting indirect things in terms of

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1 vertical integration about who -- when, indeed, they
2 saw evidence of firms integrating, they tried to back
3 out who was buying from whom based upon physical
4 location information, so sort of indirectly.

5 So on the one hand we've made enormous
6 progress, I'd say, in now really truly comprehensive
7 data sets, tracking all firms and establishments in
8 the United States, and I think it's actually still
9 underexploited. Lots of papers have been written, but
10 I think an enormous amount of things could be done.

11 The big missing pieces are P and Q and supply
12 chain, and then, more generally -- and, again, here's
13 where we could again make a -- it would be great if we
14 could somehow make progress on this. So if you're not
15 already aware, the United States, BLS, Census and BEA,
16 the three primary agencies that put together the key
17 national indicators, like GDP, they can't share their
18 microdata, and so there's great data sitting off at
19 BLS, everything from occupational data to price data
20 for that matter, that could be integrated, in
21 principle, and you can't do it right now under the
22 current legal environment.

23 So while it would be great to think about
24 partnerships and so on with the FTC, from my -- I'll
25 say from my vantage point -- and maybe even yours --

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1 if you could get at integrating the BLS, Census and
2 BEA, and I just want to mention, BEA is also sitting
3 on top of fantastic data on FDI and multinational
4 activity, and, again, that data can't be integrated.
5 So it's kind of crazy that we are almost unique among
6 the advanced economies where we're so Balkanized and
7 you can't bring all the pieces of the data together.

8 MR. PAKES: Can I say one thing?

9 MR. RAVAL: Sure.

10 MR. PAKES: So when we were doing the LRD,
11 John -- by the way, we all owe John a great deal of
12 accolades, because he's one of the guys who has really
13 gotten the data together in this country. I was there
14 at the very beginning and then did other things, and
15 John just kept doing it.

16 MR. HALTIWANGER: Some minor things like BLP,
17 right?

18 MR. PAKES: But when we were at the Census and
19 we were talking about setting up the regional data
20 centers, we had people who could go in and do this
21 stuff, there was a lawyer there, and he said, you
22 know, if one of these numbers gets out in a court
23 case, in a merger case or something like that, the
24 firm can shut down the whole Census, because -- and
25 that's the reason that they're so worried about it.

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1 I mean, I was really amazed when they let us do
2 the LRD after all that. We got this lecture on what
3 could happen if something got out, and they still
4 allowed the LRD, but it is a serious issue. I mean, I
5 would be all for -- I mean, if you could get the price
6 data at the BLS together, the BLS has very good price
7 data. I've worked on the Consumer Price Index before.
8 It's like they actually sample actual goods and all
9 their characteristics, and then they go back and
10 sample the same good again to find out what happened
11 to its price. That's how you get a price index.

12 But I don't know how, you know, you can get
13 them to merge it. The lawyers won't let you, I don't
14 think.

15 MR. GRENNAN: I mean, just one thought, harking
16 back to this issue of thinking about investment
17 incentives and all these different pieces of data. I
18 think one of the things that keeps us from doing, you
19 know, more work I think on the investment in these
20 kind of fixed or quasi fixed costs is not only -- you
21 know, it's hard on the kind of conceptual side and
22 theory side, but also difficult on the data side to
23 map these -- whatever data you might be able to get on
24 these areas into the product markets that you think
25 they're targeted at.

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1 And so I think that's another -- to the extent
2 one is asking for data or trying to construct data
3 sets, you know, that I think is another thing that is
4 very difficult and kind of connecting some of the
5 upstream costs or the kind of costs that aren't
6 necessarily well allocated to product markets that
7 they're targeted at, I think that would be a very
8 useful thing to have.

9 MR. PAKES: It's also very important for
10 vertical. When you guys are doing vertical
11 integration, that's one of the issues. The issue is
12 how the upstream guys' investment incentives
13 correspond to the downstream guys.

14 MR. RAVAL: So we've got maybe five minutes
15 left, so do any of you have any concluding remarks,
16 something you wanted to say that has not been touched?

17 MR. PAKES: I have one thing. I talk too much.
18 I have one thing, which is I really think rather than
19 focus -- I mean, I understand the focus of FTC and DOJ
20 on markups, and for short run, for things like mergers,
21 perhaps, but, you know, I think the real issue is
22 what's underlying the markups. I mean, Matt said this,
23 but, you know -- yeah, that's really the question.

24 The question isn't -- you can't answer the
25 question of whether, you know, maybe we'd increase

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1 markups, but we don't know whether that's good or bad.
2 It may well be -- you don't want to not have Google,
3 right? You might want to do things about it, okay?
4 You don't want to not have the drug companies. You
5 might want to change the rules somehow, but you don't
6 want to not have the drug companies.

7 And in order to understand either the tech
8 sector or the biotech sector, I don't think it's
9 possible to understand it without knowing more about
10 dynamics, and we're not doing that.

11 MR. HALTIWANGER: I'm fine.

12 MR. RAVAL: All right. So I had come up with
13 eight questions, and I could only ask half of them, so
14 we could probably continue this panel on for another
15 hour or two, but we are just out of time, and so we
16 will conclude.

17 (Applause.)

18 MR. ROSENBAUM: I'll just give a quick thank
19 you to everyone, our scientific committee, all the
20 panelists, moderators, discussants, presenters, thank
21 you very much, and hopefully we will see you next year
22 at the Twelfth Annual Conference. Thank you.

23 (Applause.)

24 (Whereupon, at 12:41 p.m., the conference was
25 concluded.)

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