

FEDERAL TRADE COMMISSION

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FEDERAL TRADE COMMISSION)
WORKSHOP ON:) Matter No. P085800
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THURSDAY, NOVEMBER 18, 2010

Conference Center
Federal Trade Commission
601 New Jersey Avenue, N.W.
Washington, D.C. 20001

The above-entitled hearing was held, pursuant
to notice, at 9:00 a.m.

P R O C E E D I N G S

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3 DR. ROTHSTEIN: There are some preliminary
4 announcements before we get going. I'm Paul Rothstein.
5 I'm one of the co-organizers here. If you could, as
6 always, turn off your cell phones, I would appreciate
7 that.

8 The conference is being recorded, really
9 typed up as you speak by a stenographer, so when we
10 come to the questions, we have to insist that you use a
11 microphone so that it's clear to her. She can hear
12 what people are saying, but also I would encourage the
13 speakers, if you have the choice between speaking a
14 little faster and a little slower, speak just a little
15 slower.

16 The rest rooms: You can get to the restrooms
17 without going through security if you're careful, so
18 you just have to go out the door you came in, and it's
19 a little jog to the left and then you'll find the rest
20 rooms there on your left. You will see the pathway
21 through. You'll be passing to the left of the security
22 desk, but you won't be going through the monitoring
23 gates.

24 We have Internet accessibility here. The
25 password instructions are at the registration desk if

1 you need to get into your Email.

2 Now the security briefing: If you go outside
3 the building without an FTC badge, you will have to get
4 back through by going through the whole x-ray machine
5 process again, so just a note in terms of how much time
6 that might take you. And in the event of a fire, common
7 sense things, you will get out of the building.

8 Ideally you'll head to Georgetown, across the
9 street because you'll exit the doors, it's the only way
10 you can get out, and you will go across that street,
11 and you will find yourself at the Georgetown University
12 campus. If someone is as angry at Georgetown as they
13 are at the federal government and there's trouble
14 there, then just proceed to some place safe.

15 On the other hand, there might be some
16 circumstances where it be safer to stay in the
17 building, and in that case you will be told where to go
18 inside the building. It will probably be some portion
19 of the parking garage.

20 There is the unusual request that if you spot
21 suspicious activity, please alert someone.

22 It's my pleasure now to introduce the Deputy
23 Director of our Bureau, Pauline Ippolito. Pauline
24 earned her doctorate at Northwest University in
25 mathematics. She has worked in a variety of positions

1 at the Federal Trade Commission and in the Bureau of
2 Economics. Her research and policy interests include
3 the economics of risk and information in consumer good
4 markets and the design of public policy for advertising
5 and labeling.

6 She's done a lot of work on advertising and
7 information related to health food claims in food
8 products, and right now she and I are working on a
9 project involving food marketing to children.

10 She's been involved with the Agency's fraud
11 and ID theft surveys and in general efforts to improve
12 consumer disclosures in many areas, but including the
13 mortgage markets, which is a very hot topic right now.

14 So it's a pleasure to introduce Pauline
15 Ippolito.

16 (Applause.)

17 DR. IPPOLITO: Well, first welcome. We are
18 very happy to see such an interesting crowd, and I
19 think you will agree, the program looks quite promising
20 today, so we're all looking forward to that.

21 Our Director at the Bureau would have been
22 the one introducing you and welcoming you to the
23 conference. Unfortunately, he has to go and defend the
24 merger guideline revisions in front of the ABA, so
25 that's where he is this morning, but he'll be joining

1 us later.

2 I should mention that Northwestern is our
3 cosponsor, the Searle Center from the law school and
4 the Center for Industrial Organization at Northwestern.

5 So are we going to do a program adjustment?

6 DR. ROTHSTEIN: We will do a program
7 adjustment, yes. We'll do the first panel.

8 DR. IPPOLITO: So our key note speaker is not
9 here, so we're going to change the order in which we do
10 things, so let me turn things over to Tim Daniel, who
11 is orchestrating our first panel.

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1 PANEL SESSION ONE: Disclosures and Informed Consumer
2 Choice

3 TIM DANIEL, Federal Trade Commission

4 PHILLIP LESLIE, STANFORD UNIVERSITY

5 JEFFREY BLUMBERG, TUFTS UNIVERSITY

6 DR. DANIEL: Good morning. My name is Tim
7 Daniel. I'm an economist here at the Federal Trade
8 Commission in the Division of Consumer Protection.
9 It's my pleasure to moderate this panel, which is
10 entitled "Disclosures and Informed Consumer Choice."

11 I am very pleased to have this opportunity
12 and very pleased to be able to introduce these two
13 gentleman to my left, both of whom have worked in
14 interesting ways in this area in recent past.

15 To my immediate left is Dr. Jeffrey Blumberg
16 from Tufts University. He has a Ph.D. in pharmacology
17 from Vanderbilt University and is currently a professor
18 in the Friedman School of Nutrition Science and Policy
19 at Tufts.

20 He also holds the title of senior scientist
21 and Director of the Antioxidants Research Laboratory at
22 the Jean Mayer USDA Human Nutrition Research Center on
23 Aging at Tufts University. I tried to memorize that,
24 it just didn't work out.

25 Of particular note for today's session, Dr.

1 Blumberg serves as a scientific advisor to the Guiding
2 Stars Program. The Guiding Stars Program is an
3 in-store information guidance system in supermarkets
4 designed to provide consumers with point of sale
5 information on the nutritional value of their food
6 choices, obviously designed to try to improve those
7 choices.

8 To Jeffrey's left is Dr. Phillip Leslie from
9 Stanford University. He has a Ph.D. in economics from
10 Yale University and is currently associate professor of
11 economics and strategic management in the Stanford
12 Graduate School of Business.

13 Dr. Leslie's research agenda includes an
14 examination of the role of information and in the
15 behavior of firms and consumers, and he recently
16 coauthored with two of his Stanford colleagues, Bryan
17 Bollinger and Alan Sorenson, a very interesting paper,
18 an empirical assessment of the impacts from a law in
19 New York City that compels a disclosure of the calorie
20 content of the foods offered at fast food restaurants.

21 They somehow got some very interesting data
22 from Starbucks and did some very interesting empirical
23 research on the impacts of that calorie posting law.

24 As to how I would like this hour to work, I
25 will turn the mike over to Jeffrey for about ten

1 minutes and then to Phillip for about ten minutes.
2 Then I will speak for about the same amount of time on
3 some topics.

4 Then I would like it to turn it into a round
5 table discussion. I'll pose some questions to our
6 panel members, but at that time, I would like to invite
7 everybody in the room to feel a part of that
8 discussion, and we'll recognize people to make
9 comments, ask questions and so on.

10 So if I could, I would like to turn it over
11 to Jeffrey.

12 DR. BLUMBERG: Good morning. So the topic is
13 disclosures and informed consumer choice, and one
14 approach to that is putting icons or information,
15 numbers on the Front-of-Package. I'm going to talk
16 briefly about the experience I've had with the Guiding
17 Stars Program, which is now actually a licensing
18 company selling this nutrition navigation or nutrient
19 profiling system to supermarkets across the country.

20 You heard I'm a professor at Tufts
21 University, so I'm really speaking as an academic, not
22 for the company, but I think it's a good program, and
23 so I don't mind describing it for you, but I do
24 disclose that I am on their Scientific Advisory Panel
25 and helped to develop this program, so I might be a

1 little biased. I'm also compensated for that effort.

2 Guiding Stars and another program called
3 NuVal are not technically Front-of-Package. They're on
4 the shelf tags where you see the prices. As you know,
5 the Front-of-Package belongs to the manufacturer, but
6 the shelf space and the shelf tag belong to the
7 supermarket. The intent of these two different programs
8 are the same.

9 They're really quite different in where they
10 come from, manufacturer versus retailer, and
11 nonetheless, they are considered currently by FDA as
12 being the same thing. They're Front-of-Package
13 labeling.

14 When one labels the shelf tag, as you can see
15 here and in Guiding Stars, it's this icon of a little
16 running man and either one, two or three stars or no
17 icon at all. Consumers seem to understand right away
18 what the intent was. One star is good. Two stars is
19 better, and three stars is the best in terms of making
20 a nutritious choice.

21 These tags also show up in the produce
22 department on prices or elsewhere on the shelf and for
23 things like deli products and meats and other produce
24 where the labeling, like on this oven roasted meat
25 item, will be on the weight UPC tag.

1 So Guiding Stars is a balanced approach to
2 nutrient assignments. It is based on consensus
3 science; that is, guidelines that have been established
4 by either Dietary Guidelines for Americans from the
5 Department of Health and Human Services and USDA or by
6 FDA regulations and guidelines. Where we couldn't find
7 adequate help from those, we went to the World Health
8 Organization, American Heart Association, and so on to
9 create the algorithm.

10 Very simply it is a balance score of positive
11 nutrient attributes: Vitamins, minerals, dietary fiber
12 and whole grains and nutrients to limit the negative
13 attributes like trans fat, saturated fat, cholesterol,
14 added sugars and added sodium. We get this information
15 from the nutrition facts panel on the food products
16 except where there are none, for example, on fresh
17 produce, and then we use USDA databases to develop
18 them.

19 We decided, and I would tell you other
20 programs are quite similar, on a nutrient density
21 approach; that is, it's based not on serving size, not
22 on package weight, but on one hundred KCALs, calories,
23 so it doesn't matter what the size of the package is.
24 It doesn't matter what the recommended serving size is.
25 They're all based equally, and this takes care of both

1 weight and volume issues, and we just think it's a
2 reasonable way to go.

3 It's a tiered system for each element that is
4 based on things like daily values. We have as many as
5 five or six levels with different set points, which
6 would either qualify you for one, two, or three stars
7 or no stars. The system is also designed not to
8 unfairly favor fortification, so products that just
9 have lots of added vitamins and minerals don't get
10 extra credit for adding more. And it's also got a
11 balance on the adverse side; that is, no matter how
12 many good things you have in your product, if it's just
13 filled with negative attributes, like if it's 55
14 percent sugar, the algorithm is set so that you're not
15 going to get stars even if you have whole grains and
16 vitamins in it if it's got too much of a negative
17 attribute.

18 The system was intentionally designed to be
19 simple: one, two, or three stars. Consumers understand
20 it. They can make a decision if they're choosing a
21 more nutritious product in one second. They can have
22 their kids go out and pick the starred items.

23 The consumers told Hannaford, the supermarket
24 chain in New England that originally developed that,
25 that they didn't want food police. They didn't want

1 skull and crossbones. They didn't want negative
2 messages. They just wanted something to help them make
3 a healthier choice and we felt that this approach was a
4 really simple way to do it.

5 Other systems using traffic light, using
6 multiple icons, numbers of calories, saturated fat,
7 trans fats, sugar, salt, I believe, are very
8 complicated. It's confusing. It's somewhat comparable
9 to trying to read the nutrition facts label and then
10 you have to balance it yourself: "Well, geez, it has a
11 little more salt, but it's got a lot more sugar, so is
12 that better than the one that has more sugar and less
13 salt?" The algorithm we've developed takes care of
14 that in a way that's consistent with the science.

15 It is discriminating, so currently 26 percent
16 of the products. And this is where Guiding Stars is
17 principally now: Food Lion, Hannaford, Kings, Homeland,
18 and Sweetbay, mostly along the whole Atlantic Coast.
19 100 percent of fresh fruits and vegetables get stars
20 and I will tell you we see no effect of that labeling.

21 People are not saying, "Oh, I didn't know
22 fresh fruits and vegetables were more healthy, I'll buy
23 more now." But we do see movement and I'll show that
24 you in a minute, in the center of the store, where the
25 processed and manufactured foods are. You can see

1 here, 51 percent of cereals get a star, one, two or
2 three; 50 percent of seafood; 21 percent of meat; 21
3 percent of dairy; 7 percent of soups and 7 percent of
4 bakery items.

5 I probably don't need to tell you, but soups
6 generally have lots of sodium. It takes them off the
7 stars. People were very surprised. There were a lot
8 of learning moments when we launched yogurt. "How come
9 my yogurt doesn't get stars; it's a really healthful
10 food?" Well, many yogurts have lots of added sugar to
11 it. Cottage cheese has lots of salt added to it, so
12 people were really surprised. The good news is that I'm
13 happy to tell you Guiding Stars is a discriminating
14 tool. The bad news is it may be a bit of a scathing
15 indictment about how healthy the food in our
16 supermarkets may be.

17 So we did look, between launching the product
18 which over now three years ago, at the shift in
19 products that have stars versus not. You can see that
20 we found these star induced shifts, especially in
21 frozen dinners, ground beef, and milk, getting people
22 to move from full fat to our 2 percent, 1 percent, or
23 skim milk products. Yogurt I just mentioned and ready
24 to eat cereals is where we found the biggest effects.

25 If you can read the tiny print on the

1 percentages there, you will see we had a huge,
2 whopping, statistically significant improvement in
3 moving more starred nutritious food of about 2 percent.
4 As a nutritional biochemist, I will tell you, I said,
5 "This is nothing; this is just not important. This is
6 never going to fly." On the other hand, my colleagues
7 in the supermarket were deeply impressed that this was
8 really a big change. I didn't appreciate how you're
9 supposed to do the metrics here.

10 A 1.4 percent increase that we had seen over
11 the whole store, not just the center store, translated
12 in one month to moving three million starred items out
13 the door. That translated into about one ton in one
14 month of less salt going out the door, so it can have a
15 big effect, and again this illustrates this same thing.

16 Now, we're looking here just at one month's
17 sales of ready to eat cereals before launch and an
18 after launch in about 300 stores on this one. So we saw
19 a decrease in the number of rating cereals that had no
20 stars and an increase in those that had stars. There's
21 still more non starred cereals being sold. We're just
22 seeing an increase in the starred ones and a slight
23 decrease.

24 Because these are starred on the icon, the
25 FOP had about half as much sugar, what we saw is less

1 sugar went out the supermarket doors. More stayed
2 behind, and this was equivalent to about 60,000 grams
3 of sugar not being sold during that period of time. And
4 the same is true for our algorithm, which encourages
5 whole grain and fiber. In this case starred products
6 have about five times as much fiber as those that don't
7 get a star, and as a result there was about almost
8 19,000 grams of fiber that got sold that otherwise
9 wouldn't have with this program, so we think it makes a
10 difference.

11 Guiding Stars is now licensing its nutrition
12 navigation system to high schools and colleges. They
13 now have a mobile iPhone application. This is a study
14 that was just presented at the American Dietetic
15 Association meeting two weeks ago in a high school
16 where in the cafeteria where breakfast was served, they
17 looked before and after putting Guiding Stars in. As
18 you can see, there was a slight decrease in the
19 non-starred foods, and there was an increase overall in
20 starred items.

21 So it seems to work even with high school
22 kids, and so again I just want to tell you that this
23 idea of Front-of-Package, at least in some
24 circumstances, can extend from the Front-of-Package to
25 the shelf tag, to cafeterias, to restaurants, to

1 websites and now to mobile applications where Guiding
2 Stars is going to allow you both to shop in advance and
3 know you can just bring up all the starred items on
4 your phone and so on.

5 So those are the comments I wanted to make to
6 you this morning.

7 DR. DANIEL: Thank you.

8 DR. BLUMBERG: Thank you.

9 DR. DANIEL: Thank you, Jeffrey. If I could
10 turn the microphone over to Dr. Leslie from Stanford.

11 DR. LESLIE: Thanks everybody. This is a
12 paper I'll try to summarize in ten minutes about
13 evaluating the impacts of the mandatory calorie posting
14 law that came into effect in 2008 in New York City.

15 I want to begin by maybe getting your
16 expectations down a little bit. There's a lot of
17 really interesting economic questions around mandatory
18 versus voluntary disclosure, and I know there's a
19 number of people in the room who are probably very
20 familiar with the unraveling hypothesis. It creates
21 this really interesting question for policymakers
22 around whether or not we need government intervention
23 or whether or not there's sufficient incentives for the
24 market to provide the level of information that
25 consumers would need, that there are rewards for doing

1 that.

2 There are lots of interesting questions
3 around that and I think there's research that has been
4 done and research that needs to be done to flesh out
5 some of those issues more carefully.

6 In this paper, we don't really push back the
7 frontier very much on those kinds of interesting
8 economic issues. We're motivated to do this paper,
9 because there's a lot of people out there who think or
10 who say that obesity is one of the biggest policy
11 problems facing the United States and a lot of other
12 countries around the world today, and this seems to be
13 perhaps the only really significant policy initiative
14 that is specifically focusing on trying to reduce
15 obesity.

16 As somebody that's done research on
17 information disclosure previously, in fact even in the
18 context of restaurants, although restaurant hygiene in
19 that case, it just struck me as a really interesting
20 policy question as to whether or we could provide any
21 evidence that information disclosure was going to have
22 any real traction on this big policy question, so that
23 was the reason for doing the paper.

24 It's less about fleshing out the subtle
25 economics and more about just the basic policy

1 assessment question of, "Does this look like it's going
2 to have any impact on obesity."

3 So the law came into effect in New York City
4 in 2008. It's the first place in the world that has
5 done this kind of thing, which is to say mandatory
6 calorie posting on all menus for all chain restaurants.
7 Chains are defined as any restaurant that has 15 or
8 more units nationwide and in different parts of the
9 world.

10 This law is also now being implemented, other
11 parts of the U.S. and other parts of the country,
12 around the world, sometimes the number is as low as 10
13 and sometimes as high as 20. People play around with
14 that a little bit.

15 The idea is that the calorie information is
16 supposed to be posted as prominently as price. I will
17 show you a photo in a second of what that looks like,
18 and some of you may know that actually this idea has
19 been picked up by President Obama in the health reforms
20 that were passed last March. This is going to become a
21 federal requirement now and I think we have yet to see
22 exactly the details of specifically how that's going to
23 be played out, but there is in principle now a federal
24 requirement that there's going to be a posting of
25 calorie or nutrition information on restaurant menus.

1 It's unique, by the way, because that's the
2 first time that this kind of approach has gone from
3 packaged food. We've had mandatory nutrition labeling
4 on packaged foods since the early 1990s, and there are
5 people in this room that have done a lot of research on
6 that.

7 It's the first time this has gone to the food
8 that we eat in restaurants as well, which is, as you
9 probably know, an increasing fraction of the amount of
10 calories that people are consuming these days.

11 So this is a look at Starbucks and our data
12 is from Starbucks. I'll tell you a little bit more
13 about that in a second. So you can see that it's
14 doubling the amount of quantitative information on the
15 menu. In this instance calories really are being
16 treated as prominently as price.

17 If you look at the way it's been implemented
18 by other chains like McDonald's and others, sometimes
19 you can debate whether or not it's been given exactly
20 the same amount of treatment as price has, but that's
21 for the regulators I guess to decide whether that's
22 being done.

23 We also look at some of those numbers -- and
24 you're probably wondering -- I would be wondering how
25 much you would have guessed what those numbers were.

1 Starbucks, by the way, was often identified by
2 journalists as exactly the kind of chain that was
3 likely to suffer from doing this as people are shocked
4 when they find out how many calories are in those
5 lattes and frappuccinos and so forth that they eat.

6 So it became a bit of a cottage industry for
7 journalists in New York to go and interview people in
8 Starbucks and try to capture in a colorful way the
9 shock and surprise they would have when they saw these
10 kinds of numbers.

11 Here's the information that was already
12 available at their website, so to be very clear, they
13 had already had voluntary disclosure happening in this
14 industry. It wasn't in the format that the new law
15 required it to be. It was at their website and
16 sometimes there would be brochures in stores as well,
17 and other chains did different approaches.

18 There's one chain, Subway, which had already
19 taken the approach of putting calories in their menus,
20 but they're pretty unique among chains. There weren't
21 really other chains that were doing that at all and I'm
22 going to show you this to emphasize that some of the
23 information was available. You had to go on the
24 Internet to get it. You can see that there's a lot
25 more information contained there than just calories.

1 There's a group of people that do research
2 around how complicated information like this is
3 difficult for people to understand and utilize and,
4 something that was plausible to me at least, that this
5 kind of information that we're seeing here on the
6 website is not nearly as impactful perhaps as the kind
7 of information that they have to put on their menus
8 with calories on the menus.

9 Here's another example I like to show. This
10 is the Italian chain Sbarro. The reason I like to show
11 this one is because there's this one particular item
12 there, the fettuccine alfredo, and that to me really
13 highlights the degree to which this is likely to be
14 powerful information.

15 It seems intuitive that you would expect that
16 providing this sort of information would have a big
17 impact on the behavior of consumers. On the other
18 hand, I think it's worth noting that not only was the
19 information already available for anybody who was
20 interested and wanted to know that information. Some
21 people want to know and some people don't care. But
22 secondly, when it comes to fast food and especially for
23 the chains like the McDonald's of the world, I think
24 it's reasonable to suggest that people don't really
25 care about nutrition when they choose to go and get a

1 meal there anyway.

2 I've already given up on the hope of really
3 having a nutritious meal when I make the decision to go
4 to McDonald's in the first place. People have also
5 shown extensively that people care more about price,
6 taste and convenience when they're making those kinds
7 of choices than they do about nutrition, so there's
8 reason to believe that this might not have very much of
9 an effect.

10 So we spent a lot of time trying to talk
11 Starbucks into giving us their data and after a long
12 process, that worked out okay. We also spent a long
13 time arguing with them about whether or not they would
14 let us name them, and eventually they did decide to let
15 us name them in the study, so we have pretty amazing
16 data for Starbucks, and I want to be really clear that
17 that's going to be both a strength and a major
18 limitation of the research.

19 We don't know anything about what's happening
20 outside of Starbucks. Not only do we not know what's
21 happening at other chains, I don't know what people are
22 doing when they're eating at home or other things like
23 that, and that would be in many ways, of course, better
24 to have that kind of information.

25 The strength of this data, as I'll try to

1 convince you, is it's remarkably deep, and so we can
2 say a great deal about how exactly this plays itself
3 out at Starbucks. One of the reasons we choose
4 Starbucks is because we thought that they would
5 probably be quite impacted by it and also because
6 Starbucks is just so big anyway. They're the second
7 biggest restaurant chain in the world with revenues in
8 excess of the entire movie industry and stuff like
9 that. So even if we don't say anything about anything
10 else, just about Starbucks, hopefully people would care
11 about that anyway.

12 So the data has three bases to it, and
13 there's two really that I'll mention here. We have
14 this transaction data and we have this cardholder data.
15 All of the data goes for three months before and eleven
16 months after. So posting started on April 1, 2008, and
17 we have the data for all transactions in New York City,
18 and also for control cities Boston and Philadelphia
19 where there are no calorie postings.

20 Since it's 110 million transactions, it's
21 literally every transaction at every Starbucks in every
22 one of those locations. Then they also have this
23 cardholder data set because the transaction data is
24 anonymous data, and I don't know anything about the
25 people making those transactions, although we do know

1 the locations of those transactions. We can associate
2 that with local demographic information, and so with
3 some assumptions there, you can try and talk about how
4 the effects differ by demographics.

5 The cardholder data is nice because we get to
6 follow individuals over time and there are 11,000
7 cardholders. Actually in the data set, there are
8 several million for the entire United States, but there
9 are 11,000 that are engaging in a lot of transactions
10 in New York City, Boston, or Philadelphia. That's nice
11 because you can use individual fixed effects and see
12 how exactly it impacts on the behavior of individuals.

13 This is probably the single most important
14 figure in the paper, and I'll leave it to you guys to
15 look at the paper if you're interested to see more
16 details. This is basically showing you the estimated
17 impact on calories per transaction so the vertical axis
18 here is going to be the percentage change in calories
19 per transaction, this log of calories per transaction.

20 Then the top figure is for the transaction
21 data, and the bottom figure is for the cardholder data,
22 so this is based on regression. This isn't just the
23 raw data. Here we're using our controls of Boston and
24 Philadelphia.

25 Here what we're doing is flexibly estimating

1 the impact on a week by week basis, and in the dotted
2 vertical lines is of course the moment when calorie
3 posting comes in. We don't use that information in the
4 estimation. We just put that on the figure afterwards,
5 and the top figure, you can see clearly that the
6 calories per transaction falls.

7 There's that jump up around the holiday
8 period. You don't see that jump up when you look down
9 at the cardholder data below, so we think that's mainly
10 a compositional effect in the transaction data rather
11 than impact by individuals. Anyway, no matter how you
12 slice it and whatever you do with the data, you always
13 get that there's about a 6 percent reduction in
14 calories per transaction.

15 What's interesting though is all of the
16 impact comes from food choices. The thing which is
17 probably the most surprising, the single most
18 surprising aspect of our study, is that people's
19 beverage choices at Starbucks were completely
20 unaffected by calorie posting. We tried everything we
21 could to find evidence that people were substituting to
22 either smaller sizes, from large to small or whatever,
23 or to different beverages.

24 We also have access to their milk order data
25 to see if people are more likely to switch to a low fat

1 milk or whatever, and there's just absolutely no impact
2 we can find anywhere on people's beverage choices. I'll
3 leave it to you guys to decide whether or not that's
4 something you would have expected.

5 On the one hand, you might say that people
6 are sort of inflexible in some sense when it comes to
7 their coffee choice at Starbucks or maybe that's what's
8 going on there, so all of the impact is on the food.
9 Starbucks sells less food as a result of this, and in
10 the end, calories fall from 247 average calories per
11 transaction to 232 and that's all driven by a reduction
12 in food calories.

13 We also find the effect is greater for
14 individuals that tend to buy lots of calories. With
15 the cardholder data we see that. So that's good. We
16 would hope that the people that tend to buy a lot of
17 calories would be the most affected by this kind of
18 thing. That's good news I guess.

19 However, we also find that the effect is
20 smaller for less educated and less wealthy people, so
21 that's kind of bad because we think that education and
22 wealth are negatively correlated with obesity, so that
23 says that the people that need it the most are the less
24 responsive to this kind of information as well.

25 From the point of view of Starbucks, one of

1 the nice things we can do is tell them what the impact
2 was on their profitability. There's actually some
3 neutral effect for them. Even though they sell less
4 food, that's less revenue per transaction, they
5 actually have an increase in the number of transactions
6 per day, so it seems to be driving business towards
7 Starbucks. So in contrast with what I think a lot of
8 people expected that Starbucks would be hurt by this,
9 it seems like they're actually doing okay with it.

10 We look to see how the impact differs for the
11 Starbucks that have a Dunkin' Donuts right near by
12 versus the ones that don't, and I guess it's probably
13 obvious to people here, but I always have to tell
14 people on the West Coast that Dunkin' Donuts is the
15 major competitor to Starbucks.

16 In fact, they have a pretty significant
17 positive impact at the Starbucks locations with a
18 Dunkin' Donuts nearby, which is interesting I think to
19 us because it's evidence suggestive of the fact that
20 this kind of disclosure has differential impacts for
21 different firms.

22 Some firms are going to benefit from this and
23 some firms have a negative impact from it. Remember
24 that Dunkin' Donuts is also having to post calories
25 there as well.

1 In the paper, we talk about how large the
2 magnitude is. It turns out to be pretty small. The 6
3 percent affect is unlikely, I think, to have a major
4 impact on obesity. It will have some impact, but it's
5 not going to be major, so we emphasize in the paper
6 that this is not a silver bullet.

7 We also try to talk about how it's important
8 to understand that the effect may be much larger at
9 other chains. And if the effect here is mainly on food,
10 and Starbucks is after all a beverage focused chain,
11 then if you were to extrapolate from that, you might
12 think that other food focus chains like McDonald's
13 would have a much bigger impact of this, but that's
14 clearly speculation on our part.

15 Lastly, something we all know already is that
16 so much of this is about how information is being
17 provided, so putting calories on the menu at point of
18 purchase seems to have been pretty important. The last
19 thing I'll mention is that from the interactions I've
20 had with Starbucks and from what I've been paying
21 attention to in the media and other stuff, I think it's
22 really clear these days that there's a huge focus from
23 all food companies to want to provide more nutritious
24 food.

25 So I think the reason to feel optimistic

1 about these kinds of things is that we're going to see
2 some innovation around food offerings and that the
3 supply side impacts of those kinds of things are
4 hopefully where we're going to get the most traction
5 and hopefully the biggest impact on obesity in the long
6 run.

7 Thanks.

8 DR. DANIEL: Thanks, Phillip.

9 I can't resist a quick reaction to Phillip's
10 paper in that there are some calorie postings in the
11 Washington area in certain jurisdictions. I was at a
12 Washington Nationals baseball game this summer where
13 there are no calorie postings at the Five Guys burger
14 chain offering there, which is a nutritionist's
15 nightmare.

16 And in front of me was a man talking to his
17 friend saying, "Thank goodness they don't post the
18 calories here at Nationals Park; I was out at a store
19 in Maryland, and they posted the calories, and I
20 couldn't order what I wanted."

21 And so I was curious to see whether there
22 would be any carryover affect since he knew what he was
23 buying into, but when he got to the front he ordered a
24 triple cheeseburger with all the fixings. I thought,
25 "Okay, at least he knew what he was buying, and perhaps

1 that would affect his behavior elsewhere," but the
2 information is that the evidence was there that in this
3 one instance didn't change it apparently. Maybe he
4 didn't have a four bagger, I suppose, but it didn't
5 seem to change his behavior.

6 I just want to take a few minutes to mention
7 some of the disclosure initiatives. This is but a
8 sliver of what's going on in Washington at certain
9 federal agencies with regard to disclosure issues, some
10 of them dealing with foods, some of them not.

11 Just to give you some idea of some of the
12 initiatives, three agencies that I will touch on very
13 quickly: My home agency, the Federal Trade Commission,
14 an initiative going on at the Food and Drug
15 Administration having to do with Front-of-Package
16 labeling, and an interesting memorandum was issued this
17 past summer by the Office of Information and Regulatory
18 Affairs at OMB, which oversees federal regulations in a
19 systematic way that I would just like to highlight and
20 bring to your attention, if you don't know about it
21 already.

22 The Federal Trade Commission has what are
23 called Endorsement Guides. They were first issued in
24 1980, but they were updated in 2009. The disclosure
25 issue is that if an endorser of a product has a

1 material connection to the seller, that that material
2 connection, meaning the financial connection to the
3 seller, makes money from the sale of the product that
4 consumers might not expect to be there but for the
5 disclosure, then the disclosure has to occur.

6 So in 1980, when it was first introduced,
7 some of the issues had to do with consumer testimonials
8 about the types of reactions or experiences they had
9 with diets or with other products, and the idea was
10 that consumers really ought to know whether or not
11 those endorsers have a financial reward coming their
12 way from the sale of the product.

13 The FTC wanted to extend this principle to
14 Internet commerce, and so the guides were updated and
15 released late last year, and there's been quite a lot
16 of discussion and interaction from the internet
17 commerce community and the blogosphere about how best
18 to implement what I think personally is a sensible
19 principle.

20 There's been quite a lot of discussion, and I
21 would commend for you, if you're interested in how this
22 disclosure principle might be playing out in Internet
23 commerce, to look at a June 2010 document issued by the
24 Federal Trade Commission "Facts For Business: The
25 FTC's Revised Endorsement Guides--What People Are

1 Asking," and that document provides the FTC's current
2 thinking with regard to the obligations on Internet
3 sellers as well as those who review and potentially
4 endorse those products.

5 The second initiative at the Food and Drug
6 Administration with regard to foods, not surprising, is
7 their Front-of-Package labeling initiative. This is a
8 different initiative from the, what I suspect is
9 familiar to most, nutrition label that's on every
10 packaged food product sold. This is a regulatory
11 initiative looking at possible requirements for the
12 Front-of-Package, the thing that consumers see while
13 they're going through the store.

14 Much like Jeffrey's research and Jeffrey's
15 interest in Guiding Stars, providing information
16 directly to consumers at the point of sale, this
17 initiative at Food and Drug Administration was launched
18 following the introduction and then relatively rapid
19 withdrawal of the Smart Choices label, which somewhat
20 similar to the Guiding Stars program, was an industry
21 driven program to provide incentives for manufacturers
22 to put the Smart Choices checkmark on to their package
23 if their nutritional profile was such that it
24 qualified.

25 Like the Guiding Stars program, there were a

1 lot of smart people who worked on the program,
2 nutritionists as well as industry experts. When the
3 label was introduced, however, there was quite a fire
4 storm around the Smart Choices label because certain
5 heavily sugared cereals qualified for the checkmark,
6 and as a result, there was some concern that the
7 algorithm, if you will, that underlay the determination
8 as to whether or not that food would get that checkmark
9 was flawed in not providing consumers with credible or
10 accurate or useful nutrition information.

11 So it was withdrawn and the Food and Drug
12 Administration then opened up a proceeding to gather
13 information on Front-of-Package labeling. Comments
14 were requested in April. They were due at the end of
15 July. The Guiding Stars was among those that provided
16 some comments to the Food and Drug Administration,
17 hundreds of others as well.

18 The Institute of Medicine issued a report
19 following that period, just about a month ago, talking
20 about its first phase of research of what's going on
21 with Front-of-Package labeling. That report provides
22 information on the many, many initiatives that have
23 been launched in the U.S. and in other countries on
24 Front-of-Package labeling, and just very recently the
25 GMA and the FMI, not the FLI, I apologize for the typo,

1 the Food Marketing Institute and the Grocery
2 Manufacturers of America, announced that they have
3 launched their internal initiative to provide
4 Front-of-Package labels to foods.

5 They didn't disclose exactly how their
6 algorithm was going to work or what the label was going
7 to look like, but they are seeking to be a bit ahead of
8 the curve perhaps of what the Food and Drug
9 Administration is doing, so a very active area.

10 Again the objective is to provide useful
11 information to consumers at the point of sale, the
12 difficulties being that perhaps a red light, green
13 light approach that underlay is the Smart Choices was
14 not the way to go given its costs and benefits. The
15 more tiered approach from the Guiding Stars with one
16 star, two stars, three stars seems to have potentially
17 better market success anyway. It's still out there,
18 still being used by the chains that Jeffrey identified.

19 Lastly, I just want to bring your attention
20 to this June 2010 memorandum issued by OIRA entitled
21 "Disclosure and Simplification as Regulatory Tools."
22 It is a thoughtful document seeking to lay out the
23 principles for disclosures in a regulatory setting, not
24 just for the food products at issue at Food and Drug
25 Administration, but across automobile labeling or

1 gasoline mileage standards and that sort of thing.

2 They identified the seven principles for
3 disclosures, which all federal agencies have been
4 instructed to consider when designing their disclosure
5 policies and remedies. I'll run through them quickly
6 and stop at a couple with a quick comment.

7 Agencies should identify their goals, here
8 seemingly obvious, but the take away that I took from
9 that is that if the goal is a warning that this is a
10 product you should be careful about or consume less of,
11 then you can have a little more eye catching label, if
12 you will, eye catching disclosure remedy in order to
13 get that warning across to consumers more effectively.
14 The recent cigarette pack label that Food and Drug
15 Administration is considering, I think, fits into that
16 goal of getting that warning to be very prominent and
17 eye catching.

18 Disclosures should be simple and specific.
19 They should be accurate and in plain language. They
20 should be properly timed and placed. That's going to
21 be an important and has been an important issue in
22 Internet commerce: When should consumers see a
23 disclosure if there's one that needs to be made at all
24 about the relationship between certain parties active
25 in internet commerce. Is it at the front end, at the

1 back end when they're thinking of making a purchase?

2 What's the right time for that to happen?

3 Disclosures using ratings or scales such as
4 the Guiding Stars program should be meaningful, and
5 then for the economists in the room, the agency should
6 test in advance and monitor over time the effects from
7 disclosure requirements. I think certainly I would
8 strongly agree with that, that the agencies and private
9 academicians, when they get a chance, should look at
10 the costs and benefits of these disclosure regimes or
11 disclosure proposals.

12 I will stop there, and we can then move to
13 the discussion portion of this. I would like to offer
14 my two panelists the opportunity to make comments in
15 reaction to or in amplification of their comments made
16 already.

17 Let me then turn to some questions, if I may,
18 and I would like everyone in the room to join this
19 discussion, which will take your lead as well as mine.
20 We should have some microphones in the room so I would
21 encourage you if you speak to please use those.

22 DR. LAIBSON: So this is a question for
23 Phillip. David Laibson, Harvard University. As you
24 know, there are a bunch of different research teams
25 measuring the effect of food calorie disclosures in the

1 New York case, there's Brian Ebel and his
2 collaborators. There are the New York City research
3 groups and their imperfect reports of their results. I
4 think they're still kind of working through that
5 process.

6 My impression, I just spoke to Brian actually
7 on Monday, in his own work, which was in health affairs
8 awhile ago, was that they found no effect on average
9 for a range of stores. I don't recall whether
10 Starbucks was in their data set, but they had five to
11 ten stores and they were using New York as a control
12 city, and they found literally no effect. In fact, the
13 point estimate was whether it went in the other
14 direction, disclosure insignificantly raised the
15 caloric consumption per transaction.

16 The New York City data apparently is mixed.
17 New York City seems to be reporting selected stores
18 that showed reductions in calorie consumption, but if
19 you think about the aggregate of their data, it looks
20 again like there's no effect.

21 So I guess my question to you is: What do
22 you make of the fact that on average there seems to be
23 some stores that increase caloric consumption as a
24 consequence of disclosure and some stores that
25 decreased caloric consumption as a consequence of

1 disclosure? Starbucks seems to be on the decreased
2 side.

3 Is it that we should be thinking about this
4 as a kind of failure in the aggregate, or is it that
5 somehow the Starbucks example is more indicative of
6 where we're heading? I'm wondering what your thoughts
7 are.

8 DR. LESLIE: Yeah, so one of the things they
9 did in the Ebel study did was deliberately choose low
10 income neighborhoods where there would be less educated
11 people as well. That was a specific choice they made
12 going in. We also find that the effects are smaller in
13 those neighborhoods, and their effects are small in
14 magnitude as well.

15 You simply find a positive effect, and recall
16 a large standard error, so it's not that they're
17 finding any real significant effect of any kind at all,
18 and others that have looked at this as well. I think
19 that there's a consistent theme emerging which is to
20 the extent that there are effects, they are small, and
21 we have so much data that we can get such precise
22 estimates of a relatively small effect.

23 So I think the thing we're all on common
24 ground with is that these are not large effects and
25 we're sort of quibbling over whether or not it's 6

1 percent or zero. I don't personally believe that it's
2 likely to be positive in any particular cases.

3 That seems somewhat implausible to me, but I
4 have yet to see anybody, and the health department
5 stuff has not come out yet, so we haven't seen that
6 fully, but I don't think it's plausible, based on what
7 we've seen before, that there's large effects of this
8 going on anywhere.

9 DR. BLUMBERG: I would just add a comment to
10 this in that I think time is also a factor. I think
11 it's going to take awhile for consumers to see it and
12 get used to it and so on. In the Guiding Stars, there
13 was no immediate uptick when people really did have to
14 understand it. I don't think that was the case with
15 Starbucks.

16 There was a lot of advertising. There were
17 store banners. There were shelf talkers. There were
18 website releases. They had dieticians who took
19 customers on store tours and a big effort was also made
20 to educate, to train the employees of the store, even
21 the clerks that stocked the shelves because they
22 thought customers would say, "How come my favorite
23 product doesn't have a star."

24 So we tried to give, then there were a lot of
25 employees, at least some basic information so that

1 people could respond to it. And then over a matter of
2 months, and I think the big increases that I was
3 talking about, 1 to 2 percent really were taking place
4 after about a year.

5 There are other issues that we saw in
6 Phillip's presentation, also in the supermarket. There
7 are seasonal effects. People's shopping behavior is
8 different around Thanksgiving than it is in June, that
9 sort of thing, so you need time I think to evaluate
10 these things.

11 DR. DANIEL: Yes. The gentleman to my left.
12 My apologies. The microphone is going to do the
13 talking. We'll go this way, and then we'll get to you
14 next.

15 DR. ZINMAN: John Zinman, Dartmouth College,
16 A question for Tim: So big inputs to any cost benefit
17 calculation in this domain relate to enforcement,
18 enforcement costs and enforcement effectiveness, so
19 could you just shed some light on how that FTC is
20 planning to deal with enforcement issues on these new
21 initiatives?

22 I know in the past the FTC has often been
23 charged with enforcing mandated disclosure in various
24 markets, but not always been allocated the resources
25 needed to enforce them effectively so it seems like an

1 important issue.

2 DR. DANIEL: Two things that I'll say. One,
3 I agree that it's an important issue. Two, I want to
4 make the disclosure that every FTC employee makes,
5 which is that I don't speak for any Commissioner. I
6 don't speak for the Commission. These are my comments
7 only.

8 I would say in terms of enforcement, the FTC
9 certainly has enacted, I think, a conscious and
10 pronounced information effort with regard to getting
11 information out on new initiatives. If it is the
12 Endorsement Guides for instance and their impact on
13 Internet commerce, speeches are given. Conferences are
14 attended. Disclosures are made via these things like
15 facts for business that go out to the industry and to
16 those that are participating.

17 In terms of how they're going to enforce
18 these, I'm really not in a position to tell you being a
19 relatively new economist. The economist matters as to
20 whether I can tell you what the FTC is going to do in a
21 law enforcement approach.

22 But they did bring a case in the past,
23 settled a case in the not too distant past called
24 Reverb, which was a firm that was alleged to have put
25 disclosures on to the iTunes site or endorsements on to

1 the iTunes site that were written by their employees,
2 and therefore not everyday consumers, and that was
3 deemed to be a deceptive act or practice.

4 So the FTC is watching what's going on in
5 Internet commerce. I wish I had a full answer for you,
6 but that's kind of where we're going.

7 MR. JEITSCHKO: I'm Thomas Jeitschko from the
8 Department of Justice. I have a question to follow-up
9 on the earlier question for Phillip.

10 I understand why, from the perspective of
11 studying the issue your benchmark is calories per
12 transaction, but of course from a health perspective,
13 that's not relevant unless the number of transactions
14 stays constant.

15 Do you know if any of the studies have tried
16 to look at what actually happens to caloric intake
17 across the board? In particular, you're worries about
18 if I switch from a doughnut to a bagel in the morning
19 or something like that, but then it turns out at ten
20 o'clock, I add another Snickers bar that I wasn't used
21 to eating before, and it might not do all that much
22 good.

23 Do you have any insight in that?

24 DR. LESLIE: Like I said at the beginning,
25 unfortunately one of the big limitations of the data is

1 we're not able to say anything about people's caloric
2 purchases outside of Starbucks. The one thing I can
3 say that speaks a little bit, I think, to your question
4 is that when we look at total sales of calories at
5 Starbucks, which combines of course calories per
6 transaction, total transactions, that actually ends up
7 going down by a small amount, less than 6 percent.

8 We see 6 percent reduction in calories per
9 transaction. There's a slight increase in number of
10 transactions, so the total decrease in number of
11 calories sold by Starbucks on average per day, I think
12 the number was around 4 percent.

13 That's not the same thing I know as you were
14 asking, but we don't have any data on individuals, and
15 actually I think one thing we probably need to do
16 better is tracking, getting that data and making that
17 data available to researchers.

18 DR. BLUMBERG: I would just add that when
19 the Guiding Stars program was launched in Hannaford's,
20 they had no loyalty cards, no frequent shopper cards,
21 so there was no way of tracking the individuals. It
22 was just number of items sold, but that Guiding Stars
23 program, and there are other Front-of-Package programs,
24 are now in chains that have those cards that actually
25 track everything the consumer buys in that store.

1 If you in fact shop at two different
2 supermarkets, then obviously there's no way to track
3 what everybody purchases.

4 DR. DANIEL: If I could ask Jeffrey, he and I
5 spoke briefly before the session began, and he
6 mentioned quickly in passing that some lessons were
7 learned along the way by the Guiding Stars panel, and
8 this is obviously a mix of industry and government or
9 industry and private and academic efforts, just what a
10 couple of those lessons were and what surprises you may
11 have encountered along the way. I would be curious to
12 hear that.

13 DR. BLUMBERG: I have to recall our
14 conversation earlier.

15 DR. DANIEL: You can start from scratch.

16 DR. BLUMBERG: I am a nutritional scientist.
17 I do a little bit about foods and nutrients, but I
18 really knew nothing about retail sales in supermarkets,
19 but when I was originally invited and the supermarket
20 chain said, "We hear our consumers are confused about
21 making food choices, and we think if we institute some
22 system, we will be better able to retain our customers
23 and maybe even have them spend more of their shopping
24 dollars at our store, and maybe even attract some from
25 competitors."

1 So it was a noble effort to educate customers
2 or give them information about which are your more
3 nutritious choices, but the business model was to try
4 to retain and grow their customer base, and I said,
5 "Sure. I mean, I know a lot about food. I can tell you
6 what's a good choice or a bad choice. This is not
7 going to be hard."

8 It was really difficult. It's
9 extraordinarily complex when you try to take 60,000
10 items and come up with a universal algorithm that rates
11 them all fairly and across the board. It took over two
12 years and more than two dozen iterations of refining
13 the algorithm until it was both consistent with
14 established science and made sense in the end.

15 There were lots of things to struggle with.
16 One of them is that I think virtually all of the
17 programs -- I can't speak for Smart Choices because
18 that was an industry program, so a company that put a
19 label on their box really knows what's in there -- but
20 those that are based on supermarkets relying on the
21 nutrition facts label. And the nutrition facts label
22 has some good information and it has absolutely no
23 information about many of the other things that we were
24 looking at.

25 A food label, for example, gives you the

1 total sugars. It doesn't say how much came in the
2 natural food and how much was added just to sweeten the
3 product. There's a lot of information that would have
4 been nice to include in an algorithm to do these kinds
5 of evaluations, but the information simply isn't
6 available, and no supermarket chain can go to every
7 manufacturer of every product and get that information,
8 which is proprietary to start with.

9 Tim did mention-- again I have my biases --
10 the utter fiasco of the Smart Choices program. A lot
11 of effort went into that and the industry worked with
12 the American Dietetic Association, the American Society
13 of Nutrition to get lots of endorsements and present
14 themselves as really credible. But I think, in part
15 because it came directly from the food industry, one of
16 the things they did was they developed 19 different
17 algorithms, so we just wanted to make sure that within
18 each category a formula was used.

19 So breakfast cereals were treated equally,
20 but that had no relationship whatever to bakery items
21 or to dairy items or to vegetable items, and so you end
22 up using that kind of segmented algorithm being able to
23 take a breakfast cereal that had 55 percent sugar, and
24 yet still give it a checkmark.

25 I would tell you in the Guiding Stars

1 Program, we really struggled to have a single universal
2 algorithm. It was impossible. You just cannot say
3 meat isn't as good because it doesn't have whole grains
4 in it. It's a different kind of food, and you also
5 can't use the same guidelines for infant formulas or
6 foods for toddlers. There are different requirements.

7 So we ended up with a general grocery
8 algorithm, one for meat, poultry, dairy, nuts. These
9 are all among other things naturally high fat foods. If
10 you buy vegetable oil, it's 100 percent fat, so we had
11 to look at ways to make the evaluations fair, but we
12 were even unhappy having to have four different
13 algorithms across 60,000 products.

14 So it was a huge challenge, and so too I hear
15 for the FDA and the CDC, which have commissioned the
16 Institute of Medicine to sort of look into this. I
17 don't think I need to actually warn them at all, but
18 it's not an easy issue. You just can't readily define
19 good food, bad food.

20 DR. DANIEL: Okay. Question in the back?
21 Thank you.

22 MR. RAHKOVSKY: My name is Mr. Rahkovsky, I
23 have two questions; one is for Phillip. I have a
24 question about not a thought in change of calories, but
25 the change in choices, so do you see -- because

1 information basically doubled, a lot of the
2 information.

3 Do you see less experimentation of consumers
4 so they make more choices like they did in the past?
5 Have you looked at this issue at all?

6 My second question is to Jeffrey, so you look
7 at the good or bad nutrition, but a lot of research on
8 obesity says portion controls and energy density are
9 two important issues. Do you think there is anyway that
10 these things can be incorporated in the star system
11 whatsoever, and what's the best way? what's your take
12 on that? Thank you.

13 DR. LESLIE: We didn't look very explicitly
14 at this experimentation issue. With the cardholder
15 data, we can look and see how people or how individuals
16 have changed their choices over time, and we did look
17 at that very closely. We essentially found no changes
18 certainly in their beverage choices.

19 We did not look at experimentation type
20 stuff, although my guess would be that the people who
21 have Starbucks cards are people who are very loyal
22 Starbucks customers that know exactly what it is that
23 they like at Starbucks, so it's probably not a really
24 good group of people to be looking for that kind of
25 experimentation.

1 Now, in terms of how people change their
2 choices of products more generally, on the food side
3 where all the impact is, it's worth noting, and I think
4 this is somewhat interesting, that Starbucks had very
5 few food items on offer that were less than 400
6 calories. They're not actually a lot that they
7 advertise, but they don't sell any food items that are
8 more than 500 calories in terms of their nationwide
9 offering.

10 Sometimes there are regional offerings that
11 are a little bit more than that, and for whatever
12 reason, they don't advertise that, but what that meant
13 is that if you look in the data, they have a lot of
14 foods that are all in the 400 to 500 calorie range, so
15 they didn't actually have many chances for people to
16 substitute to a 250 or 200 calorie item.

17 When I said that calories went down by 6
18 percent, it was all on the food side, and three
19 quarters of that was driven by people substituting to
20 not buying a food item, and a quarter of that is driven
21 by people substituting to a lower calorie food item.

22 So one of the things that Starbucks has done
23 in response to that is worked hard to create a broader
24 line of calorie offerings, so they now have more in the
25 200 to 300 range. That's also interesting because it

1 highlights how one of the really interesting aspects of
2 disclosure can be not just the demand side effects, but
3 the supply side effects and how it causes the firms
4 themselves to change the product offerings. I think we
5 need to do more research around that piece of it as
6 well.

7 DR. BLUMBERG: And to answer the other
8 question about nutrient density and portion control and
9 all that, those are really important things. It goes
10 beyond what I think any Front-of-Pack point of purchase
11 thing can do. I'll give you one example where I, as a
12 nutrition scientist, have sort of mixed feelings.

13 The biggest shift we saw were people going
14 from no star to one star items. We didn't see big
15 shifts going up to three stars, fresh fruits and
16 vegetables, for example. So we saw movement, people
17 bought fewer full salt, full fat potato chips, and they
18 bought baked, low salt potato chips. And I'm thinking,
19 "No, I really wanted them to buy carrots and broccoli,
20 and that's not how it worked."

21 I mean, they did make a less bad choice as a
22 result of the icons. It's not exactly moving to follow
23 the dietary guidelines for Americans, however. I do
24 think we need so much more research to evaluate this.
25 I think there's a real opportunity in using those

1 stores that have the loyalty cards that give you
2 discounts and stuff because it really tracks all the
3 food items, and they know -- I'm not sure how much --
4 who you are, so they can get much more individualized
5 data.

6 DR. DANIEL: Looking to my panel. I have one
7 more question.

8 DR. PAPPALARDO: I'm Jan Pappalardo, FTC.
9 This is really interesting research. It's really
10 important. What we regulate at the FTC on the consumer
11 side is information for the most part.

12 The one thing I was wondering about was if
13 any of you had considered looking not only on the
14 change of behavior but on the change in knowledge.
15 There's a sort of philosophical question of what is the
16 objective of disclosure. Is the objective to improve
17 consumer understanding and knowledge or is it to change
18 behavior?

19 It's quite possible that if you observe a
20 change in behavior, it may be because people did
21 understand, or maybe they misunderstood. We found in
22 our own research on disclosures that it's very, very
23 important to understand how people interpret the
24 information.

25 So, for example, if you don't see the desired

1 change in the behavior, is it because people
2 misunderstood the disclosure because it was not tested
3 on real consumers? So I'm just wondering if you have
4 any plans to do a holistic project where you look at
5 all these stages.

6 DR. BLUMBERG: Who is that addressed to? I
7 can tell you that the Guiding Stars licensing
8 corporation is interested in supporting research. I
9 think they're more interested in licensing products,
10 but to the question about information versus changing
11 behavior, I would say our primary goal is changing
12 behavior.

13 A star tells you nothing. We try to educate
14 people about what the star is based on, but we're
15 trying to get people to just make more nutrient dense,
16 nutritious choices because they see the star. We
17 actually found out, at least when the program was
18 launched, that people were doing what I like to see,
19 they looked to find out how come this has two stars.

20 They turn it over to look at the nutrition
21 facts label to see why it was better, but by and large
22 what we're finding from asking the consumers is, "We
23 just want something that's really simple, really fast,
24 really easy," so they can get in and out of the
25 supermarket.

1 DR. PAPPALARDO: A follow-up comment: We've
2 done research on appliance labeling and other things
3 where you look at stars, and people sometimes
4 misunderstand the star to think that it means something
5 beyond what the dimension is that the star relates to,
6 so to try to make sure people are really making
7 decisions that they fully understand which seems to be
8 a great place to begin.

9 DR. BLUMBERG: I think that's a really
10 interesting point, but no, we don't have that
11 information.

12 DR. DANIEL: We are going to need to wrap it
13 up. Phillip, I know you had lots to say on that
14 question. You can maybe do it in the coffee hour.

15 We would like to thank our panelists for
16 really a terrific discussion and very interesting
17 research on a very interesting area and I will turn it
18 back over to Pauline.

19 (Applause.)

20 DR. IPPOLITO: Well, it's my great pleasure
21 to introduce our keynote speaker for the morning.

22 Roman Inderst is a chaired professor at the
23 University of Goethe at Frankfurt, and before returning
24 to Germany, he was at the London School for a number of
25 years.

1 He writes in a number of areas, has fraud
2 interests, but particular corporate finance and
3 banking, competition policy, and information economics.
4 We've been following his work with great interest
5 because he's moved towards retail finance in recent
6 years, and that's obviously been a big concern of ours,
7 as you may have known from reading the papers.

8 He also has been looking particularly at
9 payment schemes in markets, how is a broker compensated
10 and how does that affect both market performance and
11 the quality of expert advice that the broker gives
12 customers.

13 Finally, let me just mention that this year
14 Professor Inderst has been awarded both the
15 Leibnizpreis prize for scientific achievement and the
16 Goshen prize, which is the German award for the best
17 economist under the age of 45, so it is my great
18 pleasure to introduce Roman Inderst.

19 DR. INDERST: Thank you very much for the
20 opportunity to talk here today, and sorry for the
21 delay. The talk today I think is very focused on
22 financial advice. I think it is nevertheless
23 interesting. I get I hope all the other areas because
24 it deals with issues of disclosure, and we've just
25 talked about disclosure in the food industry, and it

1 deals with issues of advice, and of course advice is
2 also important in our industry as well.

3 For those points here, I wanted to draw your
4 attention to the first two papers. There's a paper
5 with Mark Ottaviani, which came out in Competition
6 Policy International which takes a very generic issue
7 of advice and from a non technical perspective.

8 Next week, precisely on Monday, there's going
9 to be a presentation in Brussels, and Dave is going to
10 be there as well, of a report that we did for the
11 European Consumer Protection Agency on consumer
12 decision making in retail investment services, so there
13 is a report and experiments, et cetera, and in that
14 talk today, we will go over a little bit of this as
15 well.

16 I would like for the next 25 minutes or so is
17 to first just revisit some of the key features of the
18 market of financial services, maybe why we should think
19 about consumer protection in the first place, and
20 that's going to help me to zoom in on professional
21 advice and it's important, so it's better to make my
22 case then, and then talking about the shortcomings of
23 professional advice, of a couple of empirical and
24 particular theoretical studies, and finally draw policy
25 conclusions, if time permits.

1 First, what do we know about advice and its
2 role in the market for retail financial services?

3 Consumers' decision-making problem is
4 extremely complex. They must decide not only when and
5 how much to save, but also in which asset classes to
6 invest and, ultimately, which individual assets to buy,
7 and then how to monitor and readjust their past
8 investment choices. Their choice is made more
9 complicated by the sheer number of financial products.

10 Consumers often lack the most basic financial
11 knowledge, including knowledge of standard products or
12 of standard concepts such as inflation. In addition,
13 they may lack the cognitive and numeric skills to
14 perform the most basic financial calculations.

15 Finally, consumers may have deep-rooted
16 problems when it comes to dealing with risk, in
17 particular financial risk, and when it comes to
18 decisions that are made for the long term. Then, some
19 of the heuristics that they use in their everyday life
20 may perform badly, or consumers may excessively shy
21 away from options that they perceive as being too
22 uncertain or too ambiguous.

23 Altogether, our findings show that there is
24 potentially a large role that advice can play to
25 enhance consumer decision-making, for instance by

1 reducing complexity, by providing information or by
2 educating consumers about potential misperceptions that
3 they may entertain.

4 A web-based data collection method was used
5 in eight European Union Member States to survey 6,000
6 consumers, half of whom had purchased retail investment
7 services within the last five years [see Chapter 4 of,
8 "Consumer Decision-Making in Retail Investment
9 Services: A Behavioral Economics Perspective," Final
10 Report, November 2010]. Our survey showed that
11 consumers indeed turn to financial advice or receive it
12 when they make investments. It seems remarkable that
13 even though our survey was online, i.e., among
14 consumers who are "internet literate", still only
15 fourteen percent of purchasers of financial products
16 said that they had no contact with advisors. This
17 finding is in line with other national surveys.

18 Still, this does not tell us much about the
19 impact of advice. What if consumers obtain advice but
20 ultimately do not or need not rely on it? What if
21 advice was just a somewhat unnecessary by-product of
22 the role of brokers or other intermediaries as
23 facilitators of financial transactions?

24 We think that our research is valuable also
25 as it speaks to the real importance of financial

1 advice, and thereby suggests the importance of this
2 area for policy making. When setting up our purchase
3 process review, we took care to sample both recent
4 purchasers of financial products and non-purchasers.
5 And, indeed, there is a remarkable difference in
6 attitudes between these two groups. The fraction of
7 purchasers who trust financial advisors is 60 per cent
8 larger than the respective fraction of non-purchasers.
9 Purchasers are also much more likely to trust other
10 financial institutions or intermediaries.

11 The same picture arises when we look at other
12 questions. Purchasers are much less likely to believe
13 that financial institutions and intermediaries suggest
14 products that are unsuitable just to make a sale. And
15 purchasers are also much more likely to think that
16 their advisors have the necessary expertise and
17 knowledge.

18 When we put this data, together with a number
19 of controls, in a simple, preliminary regression, this
20 suggests that, all else equal, a customer who trusts
21 financial advice is 12 per cent more likely to purchase
22 a financial product. Financial advice and the trust in
23 it thus seem to be indeed important determinants of
24 consumers' decision making.

25 Our data allows us to go one step further. We

1 can ask for which products advice is more important.
2 Intuitively, these should be financial products and
3 services where consumers have less trust in their own
4 capability, for instance as these are particularly
5 risky or unfamiliar. Let us pick investment in the
6 stock market.

7 On average, 17 per cent of consumers in our
8 survey say that they have purchased stock or that they
9 are already invested in stock. Investing in stock may
10 seem particularly challenging for consumers who lack
11 the necessary skills and knowledge - that is, unless
12 they can rely on financial advice to bridge this gap!

13 A first, simple regression suggests that
14 trust in financial advice has indeed a particularly
15 strong effect on the propensity of less educated
16 households to hold stock. In contrast, this is much
17 less the case for more educated households.

18 For more educated households, instead, it is
19 their perception of consumer rights, rather than their
20 trust in financial advice, that has the most
21 significant impact on their decision to participate in
22 risky financial assets such as stock. This is
23 intuitive, as more educated and better informed
24 households may need to rely less on advice.

25 In terms of policy, this is an important

1 insight. Ensuring that the market for financial advice
2 works and that it is trusted by consumers may benefit,
3 in particular, households that are less capable to make
4 their own decisions. Instead, increasing consumer
5 protection more generally, or rather the perception of
6 it, may affect more the decision of self-reliant,
7 possibly more educated households.

8 These policy recommendations are also
9 supported by a complementary study that I did using
10 Eurobarometer data [see "Financial Advice and Stock
11 Market Participation," July 2010, with Dimitris
12 Georgarakos]. It supports the picture of different
13 consumer segments that rely to different extent on
14 financial advice and for which, consequently, policy
15 that is directed towards advice has different
16 relevance.

17 My comments so far point to the potential
18 positive role that financial advice can play. One
19 "bright side" of financial advice is that it can help
20 to create a more level "playing field" among different
21 consumers. But recent contributions from our literature
22 survey also point to a "dark side".

23 There is growing evidence also in the
24 academic literature that advice may induce greater
25 churning of assets and may steer consumers towards

1 products with higher fees and higher commissions. For
2 instance, one recent study that I did with German data
3 shows that, controlling for many factors, consumers'
4 reliance on a bank's advice was the most important
5 determinant of their security trading, affecting not
6 only how often they buy and sell securities, but also
7 their choice of assets.

8 When they act on recommendations and advice,
9 consumers may not be sufficiently wary about a
10 potential conflict of interest. What does our research
11 have to say on this?

12 In principle, such a conflict of interest
13 could express itself in two ways. Following a
14 recommendation, consumers could undertake a transaction
15 with a bank or a broker, even though it would have been
16 better to turn somewhere else. Alternatively, the
17 advisor may steer consumers towards particular
18 transactions.

19 The first problem seems more likely when
20 consumers purchase products through a provider's own
21 staff. Our survey indicates that this is the case more
22 than half of the time.

23 In addition, consumers seem to be largely
24 unaware of the inducements that product providers pay
25 and how these are passed on, both through commissions

1 and through implicit incentive schemes. The vast
2 majority of consumers either think that the advisor or
3 sales person through whom they made a transaction is
4 completely unaffected by such incentives or report
5 that, at the time of purchase, they did not give this
6 any thought.

7 This is particularly prevalent in the case of
8 a product provider's own staff. There, 51% of all
9 surveyed purchasers of retail investment products
10 thought that the respective employee was not influenced
11 by incentives at all and 36% reported that they did not
12 think about this when making a purchase.

13 For other sales channels the picture is not
14 too different. Again, the overwhelming majority of
15 consumers either do not think that incentives influence
16 recommendations or they ignore this issue altogether.

17 Based on casual evidence as well as our own
18 field studies, we believe that consumers both vastly
19 underestimate the importance of such incentives and pay
20 too little attention to it. Put differently, they seem
21 to be inattentive to the fact that their advisor or
22 salesperson could be biased.

23 In fact, when we asked them directly about
24 whether they think that, for instance, a product
25 provider's own staff receives contingent remuneration,

1 more than one third said that they did not think so.
2 This is not surprising, given that less than one third
3 reported that they saw written information or were told
4 so verbally.

5 In our online study we also undertook fully
6 incentivized experiments, and we supplemented this with
7 laboratory experiments using almost 500 subjects in
8 three countries. The benefits of experimental studies
9 is the ability to test hypotheses in a controlled
10 environment. In our context, this includes isolating
11 different aspects of advice [see Chapter 7 of,
12 "Consumer Decision-Making in Retail Investment
13 Services: A Behavioral Economics Perspective," Final
14 Report, November 201].

15 A situation of advice often incorporates an
16 element of trust: Based on his better or more specific
17 knowledge, an advisor makes a recommendation whose
18 merit cannot be fully verified by the advisee. We
19 analyze this aspect of advice in a setting of "cheap
20 talk". In this setting, the advisor has only privately
21 observed information about the suitability or
22 profitability of a highly stylized investment
23 opportunity. Based on this information, he can make a
24 recommendation.

25 At other times, the main task of an advisor

1 may be to produce information that the advisee can then
2 separately verify so as to judge whether a particular
3 product suits his needs. Still, an advisor may be able
4 to act strategically by selecting which information to
5 show, thereby putting emphasis on some aspects but
6 possibly withholding other information. An advisee must
7 now solve the slightly more complex task of putting the
8 information that he receives into this context: To what
9 extent does he believe that it was given to him
10 strategically?

11 Finally, even when an advisor is not better
12 informed about particular product characteristics let
13 alone the needs and preferences of a particular
14 customer, he may still be able to influence the
15 customer's decision. When talking to the customer, he
16 may stress some facts or try to play down other. Also,
17 he may try to talk the consumer out of some perceptions
18 or misperceptions that the consumer may entertain. We
19 also analyze such a setting.

20 Though these different studies span a wide
21 range of advice situations, some caveats should be
22 noted.

23 Clearly, advisors and sales people also serve
24 different functions, such as simply that of
25 facilitating transactions. Also, our set-up should in

1 no way convey the picture that an advisor can be of any
2 value in predicting market movements, helping to pick
3 particular stock, or providing any other "tips" of this
4 sort. In fact, this seems to be a common misperception
5 from which retail costumers suffer. Finally, all our
6 experiments abstract from the dynamics that could arise
7 when advisors and advisees repeatedly interact.

8 In the experiments, we varied advisors'
9 incentives. In the baseline case, advisors were paid
10 merely for participating in the experiment. They were
11 put on a flat wage. In other treatments we put advisors
12 on an incentive scheme, making their remuneration
13 dependent on the advisee's subsequent choice.

14 Precisely, when the advisee had to choose how
15 much to invest in a particular, stylized investment
16 opportunity, then the advisor was paid more the higher
17 was the advisee's investment. For robustness we allowed
18 the advisor's commission to take on various forms. I
19 will, in what follows, not dwell on these details, but
20 must refer you to the full report. I only would like to
21 mention that also the advisor's recommendations were
22 generated in the experiment.

23 In all our experiments the advisor's
24 incentives were disclosed to advisees. I take now first
25 the case of our online experiments. In the baseline

1 treatment, disclosure was provided in a neutral way and
2 in the same font size as all the other information that
3 subjects received.

4 Instead, in a second treatment advisees were
5 given, in addition, a "health warning". This read as
6 follows: "Notice that this means that the advisor did
7 not necessarily have your own investment earnings in
8 mind when he gave his advice." In a third treatment
9 this warning was given in large red font.

10 Our research questions in this experiment
11 were straightforward. How do advisees react to
12 different recommendations of the advisor, and how does
13 this depend on the advisors' disclosed incentives? And
14 how does their reaction depend on personal
15 characteristics?

16 In what follows, I confine myself to one
17 particularly stark result. In the online setting
18 subjects' reaction to a disclosed conflict of interest
19 was extremely weak. Recall that in this setting
20 advisees have to blindly trust this recommendation, as
21 they cannot verify the information that the advisor
22 privately obtained.

23 It made very little difference whether
24 subjects were told that their advisor was on a fixed
25 wage or whether he was paid proportional to what they

1 invested. Providing a mild "health warning" had some
2 impact, and providing a strong "health warning" shaved
3 another bit of the average investment. But altogether
4 these responses were very modest.

5 The outcome was even more extreme in the
6 "strategic disclosure" setting. I only want you to
7 recall from what I said beforehand that in this setting
8 it is slightly more complicated for advisees to figure
9 out how an advisor can try to influence their beliefs,
10 namely by withholding bad and only showing good
11 information. With this additional complication,
12 however, even a strong "health warning" had no impact
13 at all.

14 Let me first dispel the possibility that we
15 do not see much in the data as they are pure noise.
16 Note first that subjects did not blindly respond to the
17 questions. Indeed, they strongly react to advice. There
18 are large difference in the investment, depending on
19 whether it was done without advice, after a positive
20 recommendation or after a negative recommendation.
21 Also, we see in the data that subjects that are less
22 risk averse invest significantly more. Finally, when we
23 control for the time that subjects took for the whole
24 study we see a slightly larger effect of disclosure, as
25 those who spend more time reacted somewhat more. But

1 once again the effect remained very small.

2 Before I can draw some tentative conclusions
3 from these observations, we have to look at the outcome
4 of the laboratory experiments.

5 We had to keep down the number of possible
6 treatments that we looked into. For this reason, the
7 first key difference of the lab experiments was that we
8 provided advisees with full and precise information
9 about the advisor's compensation, depending on the
10 advisee's choice. Also, the advisee was matched in each
11 advice situation to a particular advisor, albeit
12 anonymously. In addition, in contrast to the online
13 experiment, in the lab subjects were in a highly
14 controlled environment, without distraction, and with
15 much time at hand to think through the implications of
16 their choices.

17 Taken together, these differences between the
18 online and the lab experiments account for the stark
19 difference in the outcome.

20 Given the incentives that advisors received
21 and their actual behavior, in the laboratory advisees
22 reacted strongly to a disclosed conflict of interest.
23 In fact, in some settings, which I explore next,
24 advisees exhibited even a contrarian reaction to their
25 advisor's recommendation, much like a knee-jerk

1 reaction, even though this was not justified. But this
2 knee-jerk reaction was much mitigated by communication,
3 which was another feature that we were able to analyze
4 in the laboratory.

5 In half of the treatments that we conducted
6 in the laboratory we allowed advisors to communicate
7 with advisees. This was not done face-to-face, as this
8 would have opened up channels of communication that we
9 cannot control. I come back to this later.

10 Over a certain amount of time, subjects were
11 free to communicate via their keyboards. An immediate
12 benefit from this set-up is that it allows us, still in
13 a very stylized and thus controlled setting, to see
14 whether adding some more realism in the form of two-way
15 communication makes a difference.

16 Surprisingly, communication sometimes makes a
17 difference. This is surprising as communication is not
18 face-to-face and is conducted only through a keyboard.
19 In addition, our decision problems are highly stylized
20 so that, simply put, there is not really much to
21 communicate.

22 So what difference does communication make?
23 Take the setting where we analyze strategic disclosure.
24 Recall once again that then the advisor is able to
25 affect the advisee's beliefs by withholding bad

1 information and revealing information only when it is
2 good. Thus, when an advisee expects the advisor to
3 behave strategically in this way, he should adjust his
4 beliefs accordingly.

5 This is indeed what we find when we do not
6 allow for communication. Recall that in the laboratory
7 advisees strongly reacted to the disclosed incentives
8 of the advisor. When it was disclosed that the advisor
9 had biased incentives, an advisee reduced his
10 investment by one third. But when we allowed for free
11 communication, then this reduction was smaller. While
12 we have not yet analyzed the protocols, we must suspect
13 that communication allowed biased advisors to make
14 subjects less wary, thereby mitigating the effect of
15 disclosure of incentives. Direct interaction and
16 communication may thus, even in such a stylized
17 environment, undo the implications of disclosure.

18 Recall now that we also analyze a setting
19 where the advisor has no privileged information. All
20 that is relevant is also known to the advisee. And the
21 choice setting is still very simple. So what is then
22 the potential role of the advisor?

23 This experiment used choice problems from the
24 online experiment. These problems were again framed as
25 more realistic investment decisions, with all the

1 advantages and disadvantages that this brings. The more
2 we now give up control over subjects' framing and
3 beliefs, the more there is also scope that their prior
4 perceptions or misperceptions influence their
5 decision-making, or at least their preferred choice
6 without advice. Also, subjects may become increasingly
7 insecure, in particular when financial decisions are
8 less familiar to them. Altogether, this creates the
9 possibility that advice by a second but not better
10 informed person, our advisor, can influence the
11 decision. And indeed it does so.

12 Given the time constraint, I only want to
13 bring out one result. We find that without
14 communication there is a knee-jerk reaction to an
15 adviser's recommendation. When the advisee knows that
16 the advisor benefits more from one option than from the
17 other and when this option is recommended, then he is
18 more likely to decide against this recommendation. Such
19 a knee-jerk, contrarian reaction was also observed by
20 disclosure experiments that the Federal Trade
21 Commission conducted.

22 At first this suggests a drawback of a
23 disclosed conflict of interest. It may undermine the
24 benefit of advice, making the advisee suspicious, even
25 though he need not be so in the particular

1 circumstances. However, we find that communication
2 allows the advisor to mitigate this knee-jerk reaction.
3 Hence, studying disclosure only in an environment
4 without communication would have generated potentially
5 misleading policy advice.

6 Further, our experiments of persuasion
7 suggest that while advisors can use communication to
8 their advantage and even reinforce advisees'
9 perceptions or misperceptions, communication is much
10 less powerful in talking advisees out of such
11 misperceptions. Our analysis in this regard is,
12 however, still preliminary.

13 Our studies on advice lead us to the
14 following tentative policy recommendations. Financial
15 advice should be a priority for consumer protection in
16 the area of retail investment services. It plays a
17 critical role, and in particular so for consumers who
18 are less financially capable on their own.

19 Further, policy makers should not take it for
20 granted that consumers are sufficiently wary of the
21 potential conflicts of interest in the market. This
22 holds when it comes to the commissions and other
23 inducements that advisors and sales people receive. But
24 it also seems to apply with respect to consumers'
25 perceptions of how "tied" advisors and sales people, in

1 particular product providers' own staff, are
2 incentivized, both explicitly and implicitly.

3 With respect to disclosure, policy should not
4 put too much faith in the unspecific warnings of a
5 conflict of interest. Our results suggest that
6 disclosure has not only to be clearly visible, but it
7 also has to be specific, potentially detailing the
8 precise value of an advisor's or sales person's
9 contingent payment. We are aware, however, that such
10 disclosure could tilt the market in favour of
11 vertically integrated providers, where incentives may
12 be given implicit, say through promotions or wage
13 increases. This must be born in mind, as the last thing
14 that one would want is to hamper the best ally of
15 consumers, which is competition.

16 Further, disclosing conflicts of interest may
17 not be enough and it may also not be a policy to be
18 conducted in isolation. In particular, we find that the
19 effects of disclosure may be mitigated even by the
20 communication that non-professional students conduct
21 anonymously over keyboards.

22 Our study did not look into the various
23 levers of influence activity that professional sales
24 people have at their disposal in face-to-face
25 situations. However, it must also be said that, on the

1 other hand, our study did not take into account various
2 forces that could induce a more benevolent behaviour by
3 advisors in the real world, such as self-imposed codes
4 of best practice, reputational concerns or, in
5 particular, supervision and the threat of legal action.

6 "Mystery shopping" exercises are frequently
7 performed by supervisory authorities and they have also
8 been undertaken by academics, such as already years ago
9 by Thorsten Hens from Zurich. Collecting data from such
10 exercises could represent a valuable next step, albeit
11 certainly restricted to certain providers and products.

12 Finally, as long as advisors' incentives
13 remain biased or at least frequently not in line with
14 the interests of consumers, policy makers should not
15 count on professional financial advice as a cure for
16 consumer misperceptions or other so-called "biases", as
17 we discussed them earlier.

18 To align the interests of advisors and
19 advisees, it could be envisaged to ban commissions or
20 similar inducements. A policy in this spirit seems to
21 be pursued by the UK's Financial Service Authority.

22 Clearly, before undertaking such drastic
23 steps we must be clear about what is the market failure
24 that we seek to address thereby. If the current
25 practice of how consumers pay for advice, namely mostly

1 indirectly through higher prices and commissions, is
2 grossly inefficient, why is it so prevalent?

3 Our study points to one possible source of
4 such a market failure: Consumers' ignorance or naivete
5 with respect to advisors' incentives. As I have shown
6 in work with my co-author Marco Ottaviani from Kellogg,
7 such naivete leads indeed to an equilibrium outcome
8 where advice is not paid for directly and thus remains
9 biased.

10 However, a policy of banning commissions
11 should clearly not be chosen before we cannot rule out
12 safely that it would lead itself to serious
13 inefficiencies. This could be the case when it would
14 induce consumers to excessively shy away from advice.

15 Our online experiments yield some first,
16 albeit very preliminary data on this issue. We tested
17 subjects' willingness to pay for "hard" information,
18 that is information that they saw directly on the
19 screen.

20 We were interested in situations where
21 consumers are uncertain whether to invest at all or
22 whether to switch out of existing assets.

23 In this case, when they pay for advice
24 through commissions, they only pay when they make
25 actual use of the thereby gained information. Instead,

1 when they have to pay up-front for information, this
2 payment is unconditional. It is incurred regardless of
3 their subsequent choice and thus, from consumers'
4 perspective, represents a sure "loss".

5 Some findings in the psychology literature
6 suggest that consumers may be excessively loss averse.
7 I must refer you to the report for details. Our
8 preliminary findings suggest that almost one third of
9 subjects showed behaviour that is at least consistent
10 with such loss aversion. As we have, however, seen in
11 other experiments, this may depend much on the online
12 context, which is why we would recommend to undertake
13 further studies in this direction. Likewise, it would
14 be extremely useful to make use of data collected in
15 the industry or even from field experiments.

16 In terms of policy advice, our suggestions
17 aim at supporting consumer decision making. To the
18 extent that this is viable given the complexity of
19 financial decisions, simplification and standardization
20 of information seems a key priority, given the results
21 from our experiments.

22 But this may not be sufficient, as a large
23 segment of consumers must rely on professional
24 financial advice. In this respect, our study focused
25 mainly on how to address potential conflicts of

1 interest, in particular through appropriate disclosure.
2 We did not investigate other policies such as minimum
3 qualification requirements or the imposition of
4 stricter fiduciary duties and tighter supervision.

5 Clearly, any of the policy recommendations
6 that we summarize on this final slide must be
7 considered in light of all other policies that are
8 chosen with the aim of improving the market for retail
9 financial services in the interest of consumers.

10 DR. ROTHSTEIN: We'll dispense with
11 questions, but thank you very much. We will reconvene
12 at five after the hour, please, five after 11:00.

13 (A brief recess was taken.)
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25 PAPER SESSION ONE: TOPICS IN EMPIRICAL IO

1 AVID NEVO, Northwestern University

2 PRESENTER: MATTHEW GENTZKOW, University of Chicago,
3 Booth School of Business

4 DISCUSSANT: MATTHEW WEINBERG, Bryn Mawr College

5 PRESENTER: KATE HO, Columbia University

6 DISCUSSANT: KEITH BRAND, FTC

7 PRESENTER: NATHAN MILLER, DOJ

8 DISCUSSANT: ALLAN COLLARD-WEXLER, New York
9 University

10 DR. NEVO: Let's settle down and get going
11 and try to get this thing back on time with the next
12 session.

13 DR. ADAMS: I'm Chris Adams. I'm an
14 economist here, a staff economist here at the FTC. The
15 next session is going to be chaired by Aviv Nevo of
16 Northwestern on various topics of empirical industrial
17 organization.

18 DR. NEVO: Thank you. So we have three great
19 papers, and we're going to start with the order of the
20 program with Matt going first. We'll have each paper,
21 and I guess we have 20 minutes on the paper and seven
22 minutes on the discussion, exactly seven minutes, not
23 six and a half, not seven and a half, exactly seven
24 minutes.

25 What I propose that we do all three papers

1 and then open for questions at the end on all three
2 papers, whatever time we have left, so Matt?

3 DR. GENTZKOW: All right. Thank you very
4 much, so this is joint work with Bart Bronnenberg and
5 J.P. Dube, and broadly the motivation for this paper
6 was the observation that consumers frequently are
7 willing to pay a lot to buy particular brands. This is
8 true even in situations in categories where the
9 physical products involved you would think are pretty
10 similar, and nevertheless, for Coke versus Pepsi or for
11 this kind of beer versus that kind of beer, consumers'
12 willingness to pay is high and the observation that
13 that has a big impact on market structure and on firm
14 behavior.

15 In particular the idea that if there are
16 things that firms can do that impact the formation of
17 these preferences by consumers in a long term way, that
18 would be very valuable to firms in a sense that firms
19 in the real world in fact do spend a lot of time
20 thinking about this.

21 So we're trying to understand, on the
22 consumer side, something about the origin and evolution
23 of brand preferences. There's a lot of theory that
24 speaks to where those preferences might be coming from.
25 They're models of habit formation, models of learning

1 -- I like Toyota cars because I've had some experience
2 with Toyota cars and knowing that they're good, and
3 therefore I don't know about GM cars -- models of
4 advertising, models of social influence or social
5 learning. And people have observed for a long time that
6 these kind of preferences could be a really good source
7 of market power and economic rents.

8 So in Joe Bane's original work on entry
9 barriers, he sort of speculated that these preferences
10 for branded product could be the most important of all
11 barriers to entry in markets.

12 On the empirical side, I think it's fair to
13 say we have relatively little evidence about where
14 these things come from, especially little evidence over
15 long horizons, so there are literatures trying to
16 estimate advertising effects. Those, to the extent
17 that they find any effects, the consensus is sort of
18 the effect of my ads today is gone over a horizon of
19 three or four or five months, which makes it hard to
20 tie that to anything like these long-term preferences
21 that the firms seem interested in, similarly for
22 estimates of habit formation and switching costs.

23 What we are going to do in this paper is jump
24 off from an observation that my coauthors made in an
25 earlier paper, which is if you look at supermarket type

1 products, for example, canned coffee, Folgers and
2 Maxwell House, categories where the products physically
3 are extremely similar, but the relative market shares
4 of different brands vary dramatically across space in
5 the U.S. This paper shows big circles of where Folgers
6 is popular in the west, Maxwell House is popular in the
7 east and the Midwest.

8 They argue in this paper that it was largely
9 to do with who entered these markets first a hundred
10 years ago, even though in all of these markets you can
11 now buy both of these product. So, that's a very nice
12 paper. That was their work.

13 What we're going to do in this paper is to
14 tie this to a survey that we did of about 48,000
15 households who are in the Nielsen Homescan panel, which
16 means we know all of their supermarket purchases where
17 we ask them basically, Where were you born, how long
18 did you live there, how long have you lived where you
19 live now.

20 Well, let's look at two consumers who
21 currently live in the same place, and they therefore
22 face the same availability of products. They face the
23 same prices. They face the same advertising. They
24 face the same promotion, but they differ in where they
25 lived in the past, and importantly, where they lived

1 many years ago. Say, two people who have lived in
2 Washington, D.C., 50 years ago, but one of them 50, 51
3 years ago was living in California and the other in
4 Washington.

5 At the end of the paper, I probably won't
6 have time to talk about this much, but we kind of used
7 that data to estimate a model in which consumers have a
8 stock, have a preference capital for these brands,
9 which in the model is a function of past consumption,
10 and we use that to think about the implications for
11 things like first mover advantage and market power.

12 So to preview what we find, there are big
13 effects of past experiences on current purchases. That
14 explains about 40 percent of that cross state variation
15 that they observed in the other paper. The remaining
16 60 percent, we can't say exactly what it is, but we
17 interpret that as being about differences in things
18 like prices, shelf space, availability, advertising,
19 those things, and you can see that those things are
20 correlated with those market shares in a way consistent
21 with that.

22 The second core result is these preferences
23 are extremely persistent, and so the advertising
24 literature tends to find things dissipate over six
25 months. We find even after 50 years, there's a

1 measurable significant impact of my consumption back
2 then on my behavior today, and then in the context of
3 the model, we estimate that implies big barriers to
4 entry.

5 If you get to enter the market five years
6 before I do and therefore you can accumulate the stock
7 of capital among consumers. In order to overcome that,
8 I would have to discount the price by a lot for a long
9 time to get back to parity, and we also look at -- we
10 don't say much about causality in this part.

11 But we look at how does the importance of
12 this kind of brand capital differ across categories,
13 across different types of products in the supermarket,
14 and show basically it's more important for categories
15 that are highly advertised. It's more important for
16 types of products that are socially visible, things
17 like soda and beer that you eat and drink and consume
18 with friends in a context where they can actually see
19 what the brand is.

20 We have data from the Nielsen Homescan panel.
21 This is data that lots of people use. You buy things
22 at the supermarket, and when you get home, you scan the
23 bar codes, and therefore they have a record of
24 everything that the people in the panel buy.

25 We did this custom survey asking about

1 people's migration history on top of that. We combined
2 this with some other data sources, demographics from
3 Nielson of these people, some historical data I'll talk
4 about later, and our sort of -- in fact, we used data
5 on ad intensity of these categories, and we have the
6 kind of subjective coding of social visibility.

7 So we don't know people's entire migration
8 history. We know where they were born and how long
9 they lived there, where they live now and how long
10 they've lived in their current place, and so we're
11 basically going to drop people who have a large gap
12 between those two windows, so a large fraction of
13 people either have always lived in the same place --
14 place here means state -- or have only lived in two
15 states.

16 So basically you want to think of the sample
17 as those people plus if there's kind of six months in
18 between, you think of that as basically measurement
19 error and include them as well, so we have about 38,000
20 households, of which 10,000 live in a different state
21 from the state where they were born.

22 I want to carefully tell you what the measure
23 is we're going to look at here because I'm going to
24 show you then lots of things in terms of this measure.
25 I'm going to focus in each category (so we have 230 or

1 so categories that are things like soda or baking
2 powder or whatever) on the top two brands by purchases.

3 I think of q_{i1} is the number of times
4 consumer i makes purchases of Brand 1, q_{i2} is the
5 number of times they make purchases of Brand 2. You can
6 weight this by dollars or various other things, but
7 we're just using number of purchases, and let y_{i1} be
8 the share of those top two brand purchases that are of
9 brand 1.

10 I'll call top brands share of the top two
11 brands "purchase share." Then I'm going to define, and
12 this is kind of the key measure, what we call relative
13 shares, so let μ be the average purchase share among
14 non migrants who live in Washington, D.C., and now
15 think about somebody who moved from state R to state R
16 prime. We're going to define that a consumer's
17 relative share to be their purchase share minus the
18 average purchase share they were born relative to the
19 average purchase share in their current state minus the
20 average purchase share where they were born.

21 This is equal to zero if I look just like
22 someone in the state where I was born. This is equal to
23 1 if I look just like someone in my current state. If
24 it's equal to .5, that means I'm halfway in between, so
25 this is a measure of if I look at a migrant, how do

1 they look relative to their current and birth state.

2 So this is a nice summary, and it captures
3 various hypotheses you may have. In a world where
4 there is no persistent effects of where I lived in the
5 past, all that matters for my purchases are the things
6 that would usually be in our models like prices and
7 advertising, availability and so forth. These data
8 should all be 1.

9 In a world where there's complete
10 persistence, that all that matters for what kind of
11 mayonnaise I like is what kind of mayonnaise my mother
12 used on my sandwich when I was a child. These beta
13 should all be zero, and in the kind of model that we're
14 going to describe, I'm going to write down later they
15 should depend on the number of years I've lived in this
16 place relative to the other place and the age I was
17 when I moved.

18 So if I was 60 years old when I moved, I had
19 accumulated a lot of capital so I wouldn't converge so
20 quickly. If I just moved to this place, I'll probably
21 still look a lot like people where I was born.

22 So this is -- I tend to shy away from 3-D
23 graphs, but this is a case where this is actually
24 somewhat useful. These are the betas. Raw data
25 plotted against the age at which -- this is for

1 migrants -- the age at which they moved and the number
2 of years they've been living in their current state.

3 So clearly these betas are not all equal to
4 zero. Migrants don't look like just places where they
5 came from. They also currently are not equal to 1.
6 They don't look like the people where they live. They
7 are decreasing in the age at which I moved as we would
8 expect and they're increasing in the years since I
9 moved, which we would expect.

10 So this is just projecting that on the years
11 axis, right, so somebody who just moved from California
12 to Washington is about 60 percent of the way to looking
13 like somebody from Washington so there's this immediate
14 discrete jump. This remaining gap closes steadily but
15 very slowly, so even out 50, 60 years, there's still
16 detectible differences. This is the slice against age,
17 so somebody who moved when they were very young looks
18 pretty close. Somebody who moved when they were older
19 looks farther away.

20 So all of that is from a cross-section of our
21 data, let's take migrants who moved at different points
22 in time who have lived there different amounts of times
23 for different ages. There's also a little bit of panel
24 component to this data, which is quite short. We can
25 see there's about 220 households in our sample who

1 moved during the two years that we can follow them, and
2 we can watch their purchases before and after their
3 move.

4 So if the inference is from this
5 cross-section at the right, we should expect a jump of
6 about 60 percent when they move, right, and this is
7 going to be important and I will talk it for
8 distinguishing things, like is this just selection of
9 who these people are, is this really -- is the
10 inference that the cross-section can tell us about the
11 panel really valid.

12 So if you look directly at the panel,
13 something important to say is we don't know exactly
14 when these people move, so we know people who have
15 moved in the last 12 months and the people that moved
16 between 12 and 14 months, so think about what you would
17 predict.

18 So these are people who moved between 12 and
19 14 months ago by month. Their relative share is
20 averaged over these categories, so if our hypothesis --
21 if the cross-section is right and they jump .6 and if,
22 as you would expect, when they moved within that year
23 were uniformly distributed, so if I could follow the
24 individual, their consumption would jump, but I know
25 you moved in this window but I don't know when. If it

1 was uniformly distributed, this would be linear from
2 zero to .6 and then flat or slightly increasing from .6
3 on.

4 So the precision here isn't incredible, but
5 this looks very consistent, and there's no evidence
6 that kind of back here, these people looked all that
7 different from other people in the state where they
8 were born. These are people who moved in the last year.
9 Again, the precision is not incredible, but you see
10 exactly what you would expect to see, flat. Before
11 they moved, they looked just like the people where they
12 were born. After they moved they jump ending right
13 about .6.

14 So to summarize this kind of descriptive
15 evidence, you see a jump to .6. The remaining gap
16 closes very slowly. It takes 20 years to reach .8 from
17 .6. Even after 50 years there's a significant
18 difference.

19 You see I don't really show you this in the
20 figures, but if I look at older migrants, the jump is
21 the same when they move, but the gap closes more
22 slowly. This is for, what it's worth, what our model
23 also will predict. Importantly, if you look at the
24 panel evidence, to the extent you can tell, migrants
25 look similar to non migrants before they move, which

1 argues against the idea that we're just selecting
2 migrants who are kind of intermediate in their
3 preferences and that's driving everything.

4 So you want to interpret this then through
5 the lens of a kind of a habit formation capital stock
6 type model. Everything I've showed you is just data.
7 Once we start putting it in a model, we care about
8 causality and actually interpreting these things. And
9 in particular, there are two assumptions, two kind of
10 key identifying assumptions that you need to buy in
11 order for the estimates that I showed you to be valid.

12 The first is I want to estimate the impact of
13 you living in California 40 years ago. In order to do
14 that, I need to know something about what was happening
15 in California 40 years ago. I can observe that today,
16 Coke's average purchase share in California is .6, but
17 I don't know what it was 40 years ago. If some place
18 where Coke has .6 today had .55 in the past, we would
19 be understating the extent of persistence. If some
20 places where Coke has .6 today had .8 in the past, we
21 would tend to be overstating persistence.

22 So econometrically we need expectations that
23 the past equals the present. We actually went and
24 gathered more fragmented data on the past, where we can
25 actually look at this directly, so these are across

1 state categories, purchase share in 1948 to 1968, past
2 purchase share today. There's lots of noise in these
3 data, that this Y axis of these data comes from a
4 little survey that newspapers were doing.

5 But the coefficient in this regression
6 somewhat, partly we're just lucky here, is almost
7 exactly 1, so the assumption that on average the past
8 share is equal to current shares is confirmed by this
9 data.

10 Second, we need any unobservable preferences
11 that people have for these brands to be uncorrelated
12 with their migration status. It can't be that they're
13 systematic things about people in California that make
14 them like this brand, and migrants are somewhere in
15 between.

16 We have three bits of evidence on that. One,
17 I already showed you this match between the panel and
18 the cross-section, so not only did the guys look
19 similar to the people in their birth state pre moved,
20 but it's uncorrelated with the age at which they moved.

21 Three, we looked at some brands that only
22 were introduced late, so they're saying if there was no
23 frozen pizza in the world before 1980, under our
24 identifying assumption where you lived before 1980
25 shouldn't matter. Under the selection story, it should

1 because it has information about which type you are
2 which -- and we don't find any evidence. We find where
3 you moved after these things were launched has no
4 effect to the extent we can tell, given the power of
5 this test.

6 The model is going to have basically two
7 things. One, what we call base line demand which is
8 everything that would go into demand for consumer who
9 had no prior. So, that incorporates all the supply side
10 stuff like prices and availability as well as consumer
11 characteristics that affect these preferences.

12 The other thing is this capital stock which
13 is just a discounted weighted average of your past
14 purchase shares, right, so we're modeling -- this is
15 about consumption per se, not about what ads you saw,
16 and then we assume that demand was just a weighted
17 average of these things. So the parameters we're going
18 to estimate are the weights on current stuff relative
19 to capital stock and the formation of capital.

20 So these estimates are almost just literally
21 mechanically repeating that figure. We designed this
22 model such that it's a very simple model that basically
23 captures exactly that slope that you saw with respect
24 to years, adding controls, adding this kind of
25 discounting process to separate these two things, but

1 you should have expected this almost has to be .6 given
2 that's that jump that you saw.

3 The discount factor we estimate is .975, so
4 that means for example if I get a unit of capital
5 today, it takes 27 years for half of that unit of
6 capital to decay. These are the fitted values from
7 that model, so you can see it's kind of fitting well,
8 the rough pattern that we saw, and you can look at the
9 residuals and they're not systematic.

10 So then we do some other things that I don't
11 have time to show you in detail, but we show that the
12 brand capital is more important in categories where
13 advertising is high, in the sense that that weight on
14 the brand capital term in your utility is bigger.

15 Basically that means the jump when you move
16 is smaller for these categories. Brand capital is more
17 important where social visibility is high. This
18 implies we think about these kind of counterfactuals
19 and big first mover advantage, so for example if one
20 brand has a 10 year head start, they would need to
21 discount price by 40 percent for 25 years to catch up
22 to their competitor.

23 These things last for a long time, and we
24 think this can rationalize something that was observed
25 in the other paper, which is who entered Detroit first

1 in the ground coffee category in 1900 still seems to
2 have a big effect on who is ahead today, despite wars
3 and depressions and recessions and advertising
4 campaigns and all kinds of stuff intervening.

5 So I'll stop there. Thank you.

6 DR. NEVO: Thank you. Our discussant is Matt
7 Weinberg.

8 DR. WEINBERG: Thanks. I'm not going to
9 spend a huge amount of time summarizing. You guys just
10 saw it, so this paper picks up with an earlier paper by
11 a subset of the coauthors on this one in the JPE which
12 finds that a lot of the cross-sectional variation in
13 market shares today are explained by who entered first
14 a long time ago, and that kind of begs the next
15 question of what exactly is causing this persistence
16 and this paper does a nice job of explaining what that
17 is.

18 It's able to separate out these kind of
19 supply side variables like variability and cost
20 advantages from brand preferences using the information
21 on migrants, and again the big results were that it
22 looks like about 60 percent of the gap between the
23 average purchasing pattern is explained by the supply
24 side variables, and 40 percent is explained by
25 persistent brand preferences, and that gap closes over

1 time, but it closes slowly.

2 So again several reasons were given for what
3 might be the root of this brand capital. A few things
4 that were mentioned were -- habit formation was
5 actually having consumed the goods in the past, that
6 that causes the persistence, or it can be exposure to
7 advertising or learning from others, although these
8 peer effects, having other people see you consume
9 things might matter as well.

10 I'm wondering if there might be a little more
11 on the paper that could be done to try to differentiate
12 between these different explanations, so I was
13 wondering if perhaps you could identify some products
14 that are typically purchased when you're old, and I
15 identified three, maybe they're kind of funny products,
16 but typically people haven't given a lot of thought or
17 consumed denture cleanser, hair dye and incontinence
18 products when they're young.

19 So I was wondering if the effect holds for
20 these products. If it does, then potentially it's due
21 to advertising. This isn't perfect because you're
22 probably not really high advertising markets or
23 learning from family or something else that's causing
24 the persistence in brand capital.

25 So I'm wondering if you get the fact that

1 migrants look like people from which they came for this
2 type of good. I'm not sure if you have the age of the
3 children of the households in the Nielsen data, but if
4 you do, perhaps you could look at people that have kids
5 but have them after they've moved to do something
6 similar.

7 In summary, I think I've learned a lot from
8 reading this paper, and I appreciate the fact that the
9 authors went out and collected data to answer this
10 question. I'm kind of curious about how the
11 respondents to the additional survey that collected
12 migrant status compared to the rest of the people of
13 the Nielsen Homescan data. Do they look similar or are
14 they older, younger or wealthier? And I found the
15 results very convincing and enjoyed the paper.

16 Thanks.

17 DR. NEVO: Let's move on to the next paper,
18 and then we can have questions on all the papers
19 together, so Kate Ho.

20 DR. HO: I'm going to talk about something
21 completely different, which is medical care. I'm
22 looking for physician responses to financial
23 incentives, and this is joint work with Ariel Pakes.

24 So there are really two motivations for this
25 paper. The first relates to the U.S. health reforms

1 from earlier this year, which includes among a lot of
2 other things new provisions to give physicians
3 financial incentives to control costs in the Medicare
4 and Medicaid programs.

5 So unlike in the current system where a
6 physician providing a Medicaid or Medicare, receives a
7 fee for service payment, you provide a service, you get
8 a payment for that service, the reforms will set up
9 organizations called Accountable Care Organizations
10 which will be groups of providers that are eligible to
11 share in any cost savings they make from the Medicaid
12 and Medicare programs.

13 There are also going to be pilot arrangements
14 under which physicians providing Medicaid services
15 receive bundled payments for episodes including
16 hospitalizations. So, the goal of these kinds of
17 provisions is clearly to give physicians incentives to
18 control costs, hopefully without comprising on the
19 quality of care they provide.

20 It turns out that similar cost control
21 incentives are used currently by Health Maintenance
22 Organizations, HMOs, for privately insured enrollees in
23 California, so there's an obvious opportunity here for
24 us to try to understand how physicians respond to those
25 kinds of incentives. So, that's what we're doing here.

1 There's been a previous literature that looks
2 at these kinds of issues. There are a lot of papers
3 that document lower costs in HMOs compared to other
4 types of insurers, but in general they don't look in
5 any detail at the mechanism used to reduce costs. In
6 this paper we're looking at one specific mechanism.
7 We're asking whether patients whose physicians have a
8 financial incentive to control costs receive care at
9 lower priced hospitals than other patients.

10 The second motivation is much broader than
11 this. It goes outside of the U.S. health reform.
12 There's a big previous literature that uses hospital
13 discharge records to estimate models of hospital
14 choice, and these models are important for all kind of
15 regulatory analysis, for example to predict the price
16 effects of mergers, hospital mergers or to understand
17 hospital incentives to invest in new technologies.

18 In general, the way these papers work is,
19 first of all estimate a model that asks how much
20 decision makers value each hospital, and then run
21 counterfactuals asking how much that valuation would
22 change after the merger or the investment. But these
23 previous papers in general ignore the impact of the
24 price paid by the insurer to the hospital. So, we're
25 going to address that issue. We're going to ask

1 whether the hospital choices are ever influenced by the
2 price paid by the insurer to the hospital.

3 So I've got about 15 minutes, I'm going to
4 try to get through this. I'm going to give you a very
5 quick overview of what the market looks like and of the
6 model. First of all, it's important to explain why we
7 think choices should respond to hospital prices, and
8 then I'm going to talk briefly about how we're going to
9 go about estimating this price sensitivity.

10 I'll tell you something about the data and
11 then in a bit more detail about the model. There are
12 two methods we're using. One is a multinomial logit
13 analysis that is very close to the previous literature
14 on hospital demand, and then we're developing a
15 methodology based on inequalities to address some of
16 the problems with that methodology, and I'll show you
17 some results at the end.

18 So a little bit about the market we're
19 looking at. So this is the California medical care
20 market in 2003. We're focusing on HMOs, Health
21 Maintenance Organizations, which cover something like
22 50 percent of the employed population in California.
23 The seven biggest HMOs covered 87 percent of the HMO
24 market, and we're including six of those seven, all of
25 them except Kaiser.

1 So how do physician contracts work in this
2 market? Well, other than Kaiser, outside of Kaiser,
3 the model that dominates is the California Delegated
4 Model, under which HMOs sign non exclusive contracts
5 with large physician groups. And there are two payment
6 mechanisms for these groups.

7 The first is a capitation payment system
8 under which the physician group receives a fixed
9 payment per patient to cover the services provided to
10 that patient. It turns out that under these capitation
11 payment arrangements, 89 physician groups have
12 incentives to control hospital costs, and also that
13 these incentives in general are passed down from the
14 physician group level to the individual physician
15 level.

16 The alternative payment arrangement is a fee
17 for service contract, and these much simpler contracts
18 in some sense don't generate these incentives for
19 physicians to control hospital costs. So, that's useful
20 for us in this analysis. There's capitation payments
21 under which physicians have an incentive to control
22 hospital costs, fee for service contracts under which
23 they don't.

24 So how are we going to use this analysis?
25 We're using hospital discharge data for California in

1 2003. We're focusing on women in labor; they're going
2 into hospital to give birth. Unfortunately, the data
3 set does not tell us anything about the patient's
4 physician groups and very little detail on the
5 compensation schemes used to pay these physicians, but
6 we do observe each patient's HMO and the percent of
7 each HMO's payments for primary services that are
8 capitated. There's a lot of dispersion across insurers,
9 from BlueCross/BlueShield at the low end, who banked 38
10 percent capitated payments, Pacificare at the high end,
11 97 percent.

12 So the questions we're going to ask are,
13 first of all: Are hospital choices influenced by
14 price? And secondly: Does price matter more when the
15 patient is enrolled in a high capitation insurer? By
16 assumption, does price matter more when there are
17 incentives to control costs?

18 So here's a little overview of the model
19 we're using. The idea was to estimate the utility of
20 the combined agent making the hospital choice. That
21 choice is made by a kind of composite agent, the
22 patient, the insurer and the physician. We're
23 estimating the utility of that composite agent. So,
24 where is the utility generated when the patient goes to
25 hospital is going to depend on the price paid by the

1 insurer to the hospital.

2 The second term there is an interaction. Let
3 me talk about that in a second. The third is distance
4 from the patient's home to the hospital, which has been
5 shown to be important for hospital choice, and there's
6 an arrow term at the end. I want to talk a bit about
7 this interaction term G_{pi} but this is the key for us
8 to get these estimates right and to believe that the
9 price coefficient we're estimating is right.

10 So that G_{pi} term is an interaction between
11 measures of patient severity of illness and the quality
12 of the hospital. We think it's important to get this
13 interaction term fully flexible for a couple of
14 reasons. First of all, because we think that hospitals
15 are likely to have higher quality for some sickness
16 levels than for others; secondly because the
17 preferences of a decision maker for quality are likely
18 to differ across severities.

19 If we don't get those things right, we don't
20 control for them fully, we're going to have a biased
21 price coefficient, so it's important to get that right
22 here, and I'll show you in the two methodologies the
23 extent to which we were able to do that, but again the
24 questions we're asking, first of all: Is that price
25 coefficient negative? Secondly: Is it more negative

1 when the insurer capitates physicians?

2 So the data set: I said we have hospital
3 discharge data from California in 2003. It's a census
4 of hospital discharges, so we have an observation for
5 every discharge. We're looking at privately insured
6 HMO enrollees, women going into hospital to give birth.
7 At the patient level, we observed the name of the HMO,
8 the name of the hospital, a lot of detail on diagnoses
9 and procedures and something about the price paid,
10 although it's not a perfect measure of price. I'll
11 tell you about that in a moment.

12 At the hospital level we observed the average
13 discount. That's also going to be an input into the
14 price paid, the hospital's location, teaching status
15 and detailed information about the services provided by
16 the hospital and financial statements.

17 The price variable is going to be an
18 important input into this analysis for obvious reasons.
19 Unfortunately, we don't observe the exact price paid to
20 the hospital. Instead we observe a list price, which I
21 think is equivalent to being a hotel rack rate. Every
22 year the hospital publishes a schedule of its list
23 prices.

24 Very few patients actually pay those prices.
25 Instead what happens is each insurer sits down every

1 year or two with every hospital and negotiates a
2 discount from those list prices. We observed the
3 average discount at the hospital level.

4 So we're going to calculate a price measure
5 in two steps. First we calculate an expected list
6 price, which is an average list price for ex ante
7 similar patients at the relevant hospital, and then
8 we're going to assume, at least for now, that the
9 discount is fixed across insurers. There's a lot of
10 things we want to do in the future to make this
11 estimator better, and one of the things we will do is
12 to change that assumption, but for now we're defining
13 the price as the expected list price multiplied by one
14 minus the average discount.

15 Here's something about the discharge data
16 we're using. We have 88,000 patients, 195 hospitals.
17 Teaching hospitals are a big deal of course. 27
18 percent of discharges are from teaching hospitals. The
19 average list price, once we've interacted with a
20 discount, is about \$4,000. And I'm showing you also
21 average length of stay and some probabilities of
22 adverse outcomes, which is low probability of events,
23 since very few women in the U.S. die in child birth.
24 The probability of transfer to an acute care setting is
25 about .3 percent on average. The average probability of

1 transfer to a special nursing facility after giving
2 birth is just one and a half percent.

3 I want to give you an idea of how these
4 prices and outcome measures differ by patient type, to
5 give you some idea of the variation in the data. So
6 first of all, by age. Not surprisingly, most of the
7 women giving birth are age under 40, and you can see
8 that the average price for their procedures is
9 significantly lower than that for older women. The
10 probabilities of these adverse outcomes are also lower
11 for younger women.

12 The second panel is showing you variation by
13 patient severity measured by something called a
14 Charlson score, which is a clinical index developed by
15 physicians that assigns weights to comorbidities. A
16 higher number means a sicker patient. The vast
17 majority of women in our data have a Charlson score of
18 zero. So, they're really not sick. They're just in
19 hospital to give birth.

20 About 1,800 have a Charlson score of 1.
21 About 80 have a Charlson score greater than 1. And you
22 can see that again with variation in the data is very
23 much intuitive so price increases significantly as we
24 moved from group to group. The probabilities of these
25 adverse outcomes also increased significantly from

1 group to group. So that's just to give you an idea of
2 what the data set looks like.

3 Let me move on before I run out of time and
4 tell you about the methods we're using. So first we do
5 a very standard demand analysis. This is very similar
6 to the previous literature. We're estimating by
7 maximum likelihood. The equation for estimation I've
8 written again at the top of the slide. It's
9 essentially the same as you saw before.

10 The big issue for the logits is that this
11 interaction term that I said was so important to
12 control for price endogeneity is defined much less
13 flexibly than we would like, and there's essentially a
14 feasibility issue here. The approach we're taking to
15 try to control for price endogeneity is to put in as
16 much detail in that G_{pi} term as we can. And in the
17 inequalities, you will see that essentially means
18 having something like 16,000 interaction terms in this
19 equation, and it's just not feasible in the logits to
20 do that.

21 So we're defining it in much less detail.
22 That means there's a caveat going into these results
23 that I'm going to show you in a minute, that is, we're
24 expecting the price coefficient to be biased upwards,
25 and that's what we see.

1 So when we estimate the logits for all
2 patients, we get a positive significant price
3 coefficient. That's the panel on the left. The next
4 thing we do is to split the sample. We look at half
5 the sample that's relatively less sick. When we do
6 that, we get a negative marginally significant price
7 coefficient consistent with the idea that this
8 unobserved quality that we're not doing a good job of
9 controlling for matches more for sicker patients.

10 So we get a positive significant price
11 coefficient for sicker patients, negative and
12 marginally significant for less sick patients. The
13 distance coefficient, as I said, we know distance
14 matters. It clearly matters here as well.

15 The next thing we do is to allow that price
16 coefficient for the less sick patients to differ across
17 insurers, and this is the first step we're taking
18 essentially to test our ideas about whether capitation
19 payments matter. So you can see that I'm allowing the
20 price coefficient to differ across insurers here.

21 Here's a list of the six insurers I'm looking
22 at, and I've ranked them in decrease in percent
23 capitation from Pacificare at the top to BlueCross at
24 the bottom. The estimates are on the far right of the
25 slide. You can see the price coefficients are negative

1 for the top four insurers, significantly negative for
2 two of them, and positive for the insurers at the
3 bottom.

4 So this at least is consistent with the idea
5 that price matters, but only when insurers are giving
6 physicians an incentive to control costs. In terms of
7 magnitudes, the distance elasticity implied by these
8 estimates is minus 2.7. The price elasticity for
9 Pacificare, which has the most negative price
10 coefficient, is minus .25. Price matters significantly,
11 but the magnitude of the effect here is very small.
12 Again this is consistent with the possibility that
13 there are really price endogeneity problems here.

14 So the next thing we're doing is to put
15 together a method that is going to deal with that price
16 endogeneity. And I want to take a couple minutes to
17 explain how this works. We're writing down an
18 econometrician prediction of the utility generated when
19 the patient goes to a particular hospital, so you're
20 seeing essentially that equation at the top as from
21 before.

22 There's a price term, a G_{pi} , this
23 interaction term that we need to control for and a
24 distance term, but if we change, we're now defining
25 patient severity at a more detailed level than we were

1 able to in the logits, and the G_{pi} is going to be a
2 fully flexible interaction between dummies for these
3 patient severities and hospital fixed effect. So, we're
4 defining everything in much more detail here.

5 We end up with 157 hospitals, 106 severity
6 groups. That's where the 16,000 fixed effects or
7 16,000 coefficients comes from. Given that we've
8 defined it in much more detail, we're making an
9 assumption which is that that G_{pi} terms absorbs all
10 the endogeneity problem. It absorbs all unobservables
11 known to the decision maker that effect hospital
12 choice.

13 Then the remaining unobservable is such that
14 the expectation of that error conditional on
15 instruments is zero, and that gives you a utility
16 equation at the bottom of that slide, which is the
17 utility observed by the decision maker and that's used
18 in the choice.

19 Then how does that methodology work? Well,
20 we're making a simple assumption which is that for
21 every patient who goes to hospital H, the utility
22 generated from the chosen hospital is greater than or
23 equal to the utility generated had she gone somewhere
24 else, and that's what the inequality at the top of the
25 slide says.

1 A little bit of notation, this W_{ih} , H , H
2 prime is the difference between the utility when that
3 patient went to hospital H and the utility had she gone
4 to H prime. By assumption that's non zero. And the
5 intuition for what we're going to do here, we're going
6 to find all pairs of patients who went to the same
7 insurer and had the same severity but went to different
8 hospitals. Patient ih went to H and could have gone to
9 H prime. Patient ih prime visited H prime, but could
10 have gone to H .

11 We're going to write down the inequalities
12 and add them together. Those G_{pi} terms, those
13 complicated interaction terms are going to difference
14 out because we've chosen those patients carefully such
15 that they have the same severity and the same insurer,
16 and that's the key to this methodology. Once we've
17 differenced out those G_{pi} terms, we don't have to
18 estimate them anymore. We can define them in much more
19 detail than was possible in the logit analysis.

20 Then we're going to take expectations on a
21 data generating process to address the measurement
22 term. I'm not going to talk in detail about that. I'm
23 going to show you some results from that inequality
24 analysis. Again here are the six insurers we're looking
25 at. At the top is the high capitation insurer,

1 Pacificare; at the bottom, the lowest capitation
2 insurer is BlueCross/BlueShield.

3 First I'm showing you the results using a
4 very small set of instruments. You can see that we're
5 getting a range of values for the price coefficient
6 that are consistent with the inequalities we've
7 generated. Quite often just using these instruments, we
8 have either an upper bound or a lower bound for the
9 range but not both.

10 Still there's a consistent story here, which
11 is that for the top three, it shows that for the high
12 capitation insurers, the price coefficient is clearly
13 negative. The upper bound for that range of values is
14 negative. For the bottom three insurers, that's not the
15 case. We can add more instruments and you can see that
16 now we're getting a well defined lower and upper bound
17 for the price coefficient for every insurer, and the
18 same story holds.

19 So for the insurer that makes a high
20 proportion of capitated payments to physicians, that
21 gives physicians an incentive to control costs, the
22 price coefficient is negative. Price matters in a
23 negative way. For other insurers, that's not the case.

24 Very briefly in terms of magnitudes, I showed
25 you for logits that Pacificare had a price elasticity

1 of a demand of about minus .25. For the inequalities,
2 the magnitudes are much larger. The elasticity now is
3 minus 4.1. Health Net, which has a lower proportion of
4 capitated payments, the numbers are smaller, but still
5 the magnitude for the inequalities is large, with an
6 elasticity of minus 1.9.

7 There is some comparison to the previous
8 literature. Gaynor and Vogt have a paper putting a
9 price index into the utility equation, and they get an
10 average price elasticity of 4.9. So, even bigger than
11 what we get.

12 That doesn't necessarily mean that I think
13 these magnitudes are realistic, particularly the 4.1.
14 This is something we're working on. But in general the
15 message is clear that the price seems to matter. It
16 matters particularly for high capitation insurers, and
17 when we have a method that deals with the price
18 endogeneity that we're worried about, the magnitudes of
19 the effects are large.

20 So quickly to conclude, what we're trying do
21 here to estimate the preferences of the agent that
22 determines hospital choice and identify whether
23 physician incentives affect price sensitivity. We've
24 used two methodologies. Both of them are showing that
25 price does affect hospital choice, and that it matters

1 more when the insurer is capitating a large proportion
2 of physicians.

3 We have these inequalities method, which we
4 think is kind of cool, it allows us to do a lot of
5 things. In particular we're addressing the endogeneity
6 concerns much more fully than was possible with the
7 previous methods. There are a couple other advantages
8 that I don't have time to talk about.

9 There's a lot more that we're trying to do
10 here in terms of developing this analysis, and if
11 anybody is interested, I can talk about it for a long
12 time later, but we think that the results we have so
13 far have real implications for the impact of the U.S.
14 health reforms on costs and for regulatory analysis
15 more generally.

16 So thanks.

17 DR. NEVO: Thank you, Kate. The discussant
18 is Keith Brand from the FTC.

19 DR. BRAND: I will try to make this as brief
20 as possible to keep us on time, so to summarize what we
21 just heard very briefly, this paper examines the price
22 sensitivity of a composite insurer, physician, patient
23 age on their choice of hospital using two approaches, a
24 conditional logit, and a inequality analysis. I think
25 Kate's described the motivation for the inequality

1 analysis, so I don't want to go over that again.

2 The results are intuitive in that there's
3 basically increasing price sensitivity in the degree of
4 capitation of the insurer in both. In the logit model,
5 this holds only for the sicker patients, but not the
6 least sick patients.

7 And in the inequality methods, it holds on
8 average across the population, and I'll note in the
9 paper that there are small differences in the results
10 so far when you divide the simple into less or more
11 sick patients. So I think this is very important stuff
12 for the policy questions that Kate has already
13 outlined, and for me in particular because I'm dealing
14 with these issues quite frequently in my work at the
15 Commission.

16 So I don't have many comments. The biggest
17 comment is kind of coming from the perspective of
18 someone who has an interest in this approach and would
19 like smaller information on the paper on how to make
20 the -- on how to assess how you define the groups so
21 that you know you've got the group definition correct.

22 So but one quick point, in the logit results
23 we saw the variation in the results between the less
24 sick and the more sick patients, and they pose the
25 question in the papers: Is this a result of a

1 systematic variation in preferences or is this evidence
2 of endogeneity bias? And the rationale in the paper
3 was to put more weight on the latter, that basically
4 the insurer pays the price and the insurer's
5 willingness to pay for a fixed utility benefit
6 shouldn't vary across patients.

7 I guess my initial response to that is this
8 is a composite of the preferences of the physician and
9 the patient also should matter. Even though the utility
10 benefit may be fixed across patients in the model, it's
11 probably not fixed in the underlying data generating
12 process. There's still the market utility from an
13 increment of quality. It is probably going to be
14 higher for the more sick patients than the less sick
15 patients, and I guess at the end of the day, it
16 wouldn't surprise me that you would see some systematic
17 variation in preferences, even in your inequality
18 analysis.

19 So the inequality: my big comment is on how
20 one defines the severity in price groups here. There
21 are a number of trade-offs that Katherine and Ariel
22 have outlined in the paper. You define the severity
23 groups in a way so they're refined enough so that you
24 can plausibly say that any remaining price variation is
25 going to affect choices, but there's no correlated

1 variation and unobservable quality that may affect
2 choices as well, which would bias your price estimates.

3 So you want to set up and refine the
4 groupings, the severity groupings in a very refined
5 way, but not so refined that you wipe out all the price
6 variation so there's some trade-off on that.

7 Within severity groups, you define price
8 groups so then again you can plausibly say all the
9 variation in price within severity groups affects
10 choice, but is not correlated with unobserved quality,
11 and there are a number of --there are some measurements
12 issues here.

13 If you define the price groups too broadly,
14 there are aggregation issues. If it's too narrow,
15 there are some measurement error concerns. And again
16 you want to pick the price grouping so that you
17 maintain some variation within the severity group.
18 That's a poorly worded bullet. You want to maintain
19 price variation within severity groups, not price
20 groups because you're going to compute an average price
21 within price groups.

22 So again my question in going over this paper
23 was: How do you know that you got the right balance?
24 How do you know that you're not wiping out so much of
25 the price variations that you're getting kind of a

1 precision on the bound? How do you know that you've
2 defined the severity groups in such a way so that you
3 really can say that there's no endogenous variation?

4 So in the paper they talk about -- so the key
5 distinction kind of, this is maybe too crude a
6 description, so basically within severity groups, they
7 look at the variation of co-morbidities across price
8 groups, and the question is: Does the co-morbidity or
9 does the variation in co-morbidity within price groups
10 explain choices. And they relied on the opinion of
11 outside experts which basically said no, which is of
12 course very valuable.

13 They did an analysis of variance on the
14 outcomes, the probability of mortality, the probability
15 of transfer to another facility. Does moving from
16 severity groups to price groups explain additional
17 variation in these outcomes? And if it doesn't, then
18 it's probably reasonable to say that you've wiped out
19 all the endogenous variation that's coming out of
20 prices.

21 So I guess what I would appreciate more is
22 how much -- what is the incremental explanation, what
23 is the incremental -- how much of the variance on
24 outcomes is explained by prices? And you say that it's
25 small, but I guess I would like to know how small is

1 small enough for you to be comfortable with that.

2 In addition, once you've defined these
3 groups, they look at the -- how much of the overall
4 price variation is explained additionally within price
5 groups going from severity groups to price groups, and
6 it's 12 percent here. So, that doesn't strike me as
7 implausibly small, but I guess at what point would you
8 have considered that too small to say, "Yeah, I have
9 the right amount of price?" Or if it's too small,
10 would you back off or further refine the pricing groups
11 so that you can see that you're generating more price
12 variation?

13 Alternatively it seems plausible to me that
14 if instead of 12 percent, you have 60 percent, you
15 might be concerned that maybe the definition of the
16 severity groups wasn't sufficiently narrow to actually
17 filter all the price endogeneity. So, there are a lot
18 of moving parts it seems to me at this point in setting
19 up these things, and it seems very critical because my
20 guess is the results are very sensitive to exactly how
21 you define this stuff.

22 So that's my big broad comment. Let me make
23 three smaller points, if I can get this in. So you
24 have this constant variance on the bounds, and I'm
25 putting variance in quotes because obviously we're not

1 talking about classical inference here with a
2 covariance matrix, but you know get some commentary
3 results on the CIGNA observation. You get a positive
4 lower bound on the price coefficient, and you know
5 that, well, this could be attributable to the fact that
6 we have a smaller sample size for CIGNA and so you can
7 get a noisy measure.

8 So then it occurred to me that if that's a
9 relevant thing, then maybe we should be thinking of
10 some concept of dispersion around these bounds. And I'm
11 not sure exactly how you do that, but the most obvious
12 thing that came to my mind was bootstrapping,
13 presenting a bootstrap distribution on the bounds.

14 Second, price elasticity comparison to logit,
15 because in the paper you dump the lower bound on the
16 two pairs, what they are into the logit model, and I
17 wasn't sure why you would want to do that.

18 I'm guessing you took this into account but
19 it wasn't explicitly in the paper, that you normalize
20 the price coefficient differently so in the
21 inequalities model, you normalize it by the distance
22 coefficient, and the logit obviously is normalized by
23 $\pi \text{ root } 6$.

24 But what occurred to me is that you could
25 simply stick the price change into the equation 14 and

1 count the number of switches, and that would be
2 something a little more straightforward.

3 Finally, as Katherine noted they see hospital
4 prices at the hospital level and not the hospital
5 insurer level and pose the question at the end: Could
6 our results be explained by simply this measurement or
7 could it also be explained if higher capitation
8 insurers negotiate smaller discounts, although the
9 sequels only present some regression results that
10 suggest otherwise?

11 I think my standard intuition is that it's
12 got to be true, all else equal, that hospitals should
13 be compensated for bearing additional risk. So, how
14 could one would address that in the regression model?
15 The most obvious thing that comes to my mind is that
16 the variation of the relative bargaining positions that
17 may explain why some plans are higher capitated and
18 also able to pay hospitals at a lower rate.

19 So I'm not sure how exactly one could address
20 that, but I guess you would have to look at the
21 regional variation to look at how much competition each
22 hospital has or how many close ups each hospital has
23 and maybe account for that in some way.

24 So those are my comments.

25 DR. HO: Do you want me to comment now?

1 DR. NEVO: If you want like in 30 seconds, if
2 you think it's really important to do it now and not
3 later. Maybe you will get a chance later.

4 The last paper is Nathan Miller.

5 DR. MILLER: I want to talk today about
6 modeling and estimating models of spatial competition.
7 This is joint work with my coauthor Matt Osborne, and I
8 should say at the outset that my views that I'm
9 expressing today are my own and shouldn't be purported
10 to reflect those of the Justice Department or the BEA.

11 I'm going to start with I think the
12 uncontroversial statement that firms in many industries
13 are geographically differentiated. I've thrown a
14 couple up on the slides, and this fact that there has
15 been some competition in these settings has motivated a
16 number of seminal theoretical papers.

17 I think folks are familiar with the Hotelling
18 line. This stuff goes way back. Though there hasn't
19 been a lot of structural work on the industry, and what
20 Matt and I wanted to do is construct an estimator that
21 lets us estimate the underlying parameters of demand
22 and supply in these models. And do so using variation
23 that as economists, we may reasonably be able to, using
24 data that we can get our hands on.

25 So, for instance, the estimator we're going

1 to introduce can estimate the parameters of fairly rich
2 models using data on maybe regional average prices or
3 total consumption and production in various areas or
4 firm level data. We think that the structural
5 estimation of these models is interesting and could be
6 used in a number of different settings.

7 First of all, we could get a grasp simply on
8 how much firms are indeed spatially different and how
9 much local market power exists in industries. And also
10 it could enable new counterfactual policy experiments.
11 One could use the model to conduct hypothetical
12 monopolist tests and construct geographic antitrust
13 markets.

14 An interesting question might be how carbon
15 taxes or gasoline taxes might affect localized market
16 power on these industries or how imports and tariffs
17 are likely to affect consumers across a large nation or
18 you can plug this estimate more into a dynamic model
19 and start asking questions related to entry deterrence
20 or related topics.

21 So I want to start by motivating the paper
22 with a simple question: Why is this challenging? The
23 most obvious way to estimate the cost of transportation
24 is simply to observe the distribution of market shares
25 and how they change over space. So, on the slides I put

1 up a little plot. The star is meant to represent a
2 firm, and one could imagine the shades of blue
3 representing the market shares of the firm.

4 This firm captures high market shares among
5 nearby consumers, and the market shares attenuating in
6 the distance. Maybe this is a movie theater or a gas
7 station or something like this. If you have these
8 data, then one can write down a model and simply select
9 a parameter calling it transportation costs and
10 rationalize the distribution of market shares.

11 Matt and I like to talk about a data
12 availability problem, which is that distribution of
13 market shares are typically not observed in the data,
14 at least the data that as economists we have access to,
15 and we're not actually aware of any studies that make
16 use of distributions of market shares.

17 More commonly, it would be firm level shares
18 or prices. I also want to note that in some industries,
19 especially business to business industries, firms
20 exercise spatial price discrimination. For example,
21 they might charge higher prices to nearby captive
22 demand. When spatial price discrimination is used,
23 then one would also need to be able to account for the
24 spatial distribution of prices, which just makes this
25 problem more pronounced.

1 So the paper really has two parts. The first
2 part is we write down an estimator for a model of
3 spatial price differentiation, encompassing spatial
4 price discrimination that can make use of different
5 data, different balances of observation. And we think
6 that the estimator potentially allows us to -- allows
7 econometricians to extend their models, to extend the
8 estimation of models to settings that previously would
9 have been too demanding or too hard to do. We're going
10 to get some conditions whereby the estimator is
11 consistent and not systematically normal.

12 The second part of the paper is an empirical
13 application to Portland Cement. Cement fits the model
14 well in some sense. It's relatively homogenous aside
15 from the geographic component. I'll talk more about
16 that later on, but our main goal is to show the
17 estimator works well in this one real world example.

18 We provided fits that are I think pretty
19 impressive both in sample and out of sample, and it
20 also lets us highlight some of the counterfactuals one
21 might be able to do. So, it allows us to do merger
22 simulation in which we show how merger harm is
23 distributed across California and Arizona and how
24 different divestitures affect not only the total harm,
25 but the geographical distribution of harm.

1 The main methodological insight here is that
2 you can essentially use numerical approximations to
3 equilibrium to relax the data requirements of the
4 estimator. So basically leveraging the information in
5 some supply and demand model for a given parameter
6 vector, a parameter vector, i.e. compute the prices and
7 the market shares that characterize equilibrium given
8 the model, given the candidate parameter vector.

9 With the disaggregate shares and prices one
10 can aggregate equilibrium predictions at the level of
11 the data. So, for example if one has data on average
12 prices in California, after computing equilibrium, one
13 might have average prices for each consumer in
14 California, and you just average that up to get the --
15 to construct the aggregate prediction of the level of
16 the data.

17 Since this is repeatable, we can do that for
18 any parameter vector, so we can select the parameters
19 that match the predictions to the data. Intuitively the
20 way this estimator works is that you have some sort of
21 nested logit in which you minimize an objective
22 function, you have to compute equilibrium and then
23 aggregate the equilibrium predictions to the level of
24 the data.

25 The key assumption for identification is that

1 when evaluated at the underlying population parameter
2 vector, the differences between the predictions of the
3 model and the underlying data are due to measurement
4 error. For example in an application on data that are
5 collected by the U.S. Geological Survey, sometimes
6 plants don't report their information to the USGS, so
7 that creates a measurement error.

8 We're attributing differences between the
9 predictions and the data to measurement error, and
10 we're assuming that that measurement error is going to
11 be orthogonal to plant locations and the cost and
12 demand shifters. Given those assumptions, you can
13 derive what essentially amounts to a multiple equation
14 nonlinear least squares estimator. The left-hand side
15 of this are essentially the data. The twist is the
16 right-hand side of the model predictions are computed,
17 so the right-hand side of this is based on equilibrium
18 computations rather than data itself.

19 Intuitively each equation in the least
20 squares estimator matches a times-series of data, for
21 example, the average prices in California to the
22 corresponding prediction, equilibrium prediction.

23 I'm going to start by describing a little bit
24 an economic model, and then we'll talk about how to
25 take this to the data. We start with a notion of

1 geographic space which is some area, and plants have
2 fixed locations. Consumers exist over the space, and
3 then we're going to introduce the notion of a consumer
4 area, which is a subset of the space. And each firm is
5 going to be able to set a different lower price to each
6 area, and consumers are going to bear the cost of
7 transportation.

8 The consumer areas allow us to build in
9 spatial price discrimination. So, each specification
10 determines how much of the area us discriminated. For
11 example, if there's only one consumer area, then
12 there's no discrimination, but if there's lots of
13 areas, you have discrimination.

14 This is an example of one geographic space.
15 There are three consumers areas and two firms. Each
16 firm is setting three different prices, a different
17 price to each consumer area.

18 So the supply model is fairly
19 straightforward. Firms are maximizing variable profits,
20 which is just the price times quantity in each consumer
21 area indexed by N , and then less variable costs which
22 is just you can integrate up over a plant specific cost
23 curve. We need the cost curve to be continuous
24 differentiable, but potentially you can capture things
25 like increasing marginal costs or capacity constraints

1 flexibly.

2 Demand within a consumer area we're going to
3 model using a conventional discrete choice system. The
4 indirect utility is just going to be a function of the
5 price that's charged in the area, the average -- the
6 average distance between the consumer area and the
7 plant.

8 Now, if the error term is logit or nested
9 logit, then one gets analytical expressions for market
10 shares, and that's going to facilitate the computation
11 of equilibrium quickly.

12 You get standard first order conditions here,
13 and this is really the key to the model, and one can
14 characterize equilibrium as just a mapping from the
15 parameters of the model into a vector of prices such
16 that the first order conditions hold. We're going to
17 assume that this equilibrium is unique and that it
18 exists. And I'll come back to this: Why it was so
19 important?

20 So given the structure of this model, what we
21 want to do is we want to recover the underlying
22 parameters. I'm going to denote the endogenous data as
23 a vector Y^T . This includes average firm prices or
24 production or anything else like that.

25 I'm going to denote the aggregated

1 equilibrium predictions as Y tilda. That will be a
2 function of the parameter vector as well as the vector
3 X , which will include plant locations and cost and
4 demand shifters and things like that.

5 The estimator takes the following form: I'm
6 just going to minimize the squared deviations between
7 each of the equations and the equilibrium predictions,
8 potentially weighting where appropriate between the
9 different equations.

10 As I said before, this really amounts to
11 non-linear least squares, and once you get here, this
12 is textbook. You can open up Green, and there's a
13 description of this. The twist is the right-hand side,
14 the Y tildas are computed, and what I do is we just
15 basically select a price vector that makes the first
16 order equations almost whole, at least very precisely
17 to a small -- so errors are small, so we use a
18 tolerance one minus 13. To actually define this non
19 linear, we use DFSANE, and we can end up doing an
20 iteration in two to ten seconds or so.

21 If a unique Bertrand Nash equilibrium holds,
22 exists, and the population parameters vector is
23 identified, then the NLLS estimator is asymptotically
24 normal. A couple comments: One is that there is the
25 uniqueness of existence so the logit is in multiple

1 firms but it's not generally a property of the models
2 we're looking at.

3 The second is that the population parameter,
4 the aggregation procedure can obscure identification.
5 So, even if one had disaggregate data, potentially you
6 use the identification of the ideation process. Matt
7 and I talk about how you can potentially test some of
8 these assumptions empirically.

9 The empirical application is Portland Cement.
10 Cement is defined as a finely ground powder. You put
11 it with water. You get ready mix concrete. You ship
12 it by truck. Consumers pay a transportation cost.
13 Contracts are individually negotiated.

14 This is a map of the area we looked at.
15 Plants are in blue. Imports flow in through San Fran,
16 LA, San Diego and Nogales. This model also captures
17 the foreign imports. There's very little inflow or
18 outflow from this area to other domestic areas, and so
19 you really you do get a geographic space in the sense
20 of the model.

21 We use a marginal cost curve that bends
22 upwards at some point that we estimate. Demand is
23 specified with nested logit where we put the outside
24 goods in a different nest. We use 90 counties within
25 Arizona, Nevada, California to specify price consumer

1 areas, which of course has a fairly fine price
2 discrimination, and we model importers as being a
3 competitor fringe.

4 The data we end up using are average prices
5 in three regions: Total production in those regions,
6 total consumption in each of those four states, and we
7 also make use of the little information on the cross
8 region shipments. So, we end up with essentially ten
9 non linear equations over 21 time periods spanning 1983
10 to 2003.

11 Here's the model. We can see in panel A we
12 look at the regional consumption. On the left-hand
13 side is the data. On the right-hand side is the model
14 prediction that the estimates have produced, and we can
15 see we've explained about 93 percent of the variation.

16 Panel B looks at production. We're
17 explaining 94 percent of the variation there. Panel C
18 is the 82 percent of prices, and panel D is this out of
19 sample, which has 98 percent of the region, cross
20 region shipments.

21 We're able to do some neat things like this.
22 This is the distance the cement is shipped over across
23 the space. This is plots of the business so there's a
24 plant here with a star, and you can see how its prices
25 go down to consumers that are more distant, and as do

1 its market shares. This plant, which is just north of
2 Phoenix, seems to have a fair amount of low price
3 market power.

4 Here you can see that that merger harm is
5 concentrated around LA and Phoenix diminishes
6 elsewhere. And in Map B, we've examined the merger harm
7 under one potential divestiture plan in which we divest
8 one plant in the LA area, and one can see that it
9 mostly mitigates harm in southern California, but not
10 much in Phoenix.

11 Let me go through this just to finish. One
12 is that our mix uses the estimator in a static model,
13 but the estimator could also define stage game pay offs
14 in more dynamic routines, so essentially one could plug
15 it into maybe an estimator by Bajari, Benkard, and
16 Leven and things like that.

17 I think some of the interesting questions
18 that would enable economists to answer is to look at
19 firm location choice and ask the question how firms
20 should ultimately locate to deter entry or whatever.
21 You would have to solve the state-space problem to get
22 that done, but we think it's potentially an interesting
23 extension.

24 Second, there's a parallel here to estimators
25 for product space differentiation. And you can

1 intuitively take BLP: When you run BLP, generally what
2 you get is you fully observe prices versus market
3 shares at that level, but you don't observe all
4 characteristics, for example quality.

5 In our model, you fully observe the
6 characteristics, but in the data you don't observe all
7 the prices or market shares. Instead what you observe
8 is aggregated. In both cases we're using numerical
9 techniques to cover unobserved metrics, and then enable
10 us to make sure there's a minimization of an objective
11 function.

12 So that's it.

13 DR. NEVO: Thank you. Our discussant is Mr.
14 Cement himself, Allen Collard-Wexler.

15 DR. COLLARD-WEXLER: I want to start off with
16 just some review of why we think spatial markets might
17 be important and difficult to analyze.

18 So the central issue that we have with these
19 spatial markets is that essentially there is market
20 segmentation, but the markets overlap with each other.
21 So, even though I might be a cement plant over here,
22 and I might only compete with cement plants that are
23 around me, those plants compete with other plants that
24 are located further away and so on.

25 So rapidly, kind of solving out equilibrium

1 in spatial markets has this problem of dealing with
2 neighbors' neighbors, and the state space becomes huge.
3 This is an unfortunate problem, given a lot of markets
4 we hear about have some spatial segmentation. This is
5 clearly true for cement, and it's true for a lot of
6 other bulk commodities, things like coal or chemicals,
7 for instance, electricity as well in a much more
8 complex way. These are important market power issues to
9 get a handle on and they're difficult.

10 What I've been trying to summarize on the
11 paper and what I want to focus in on is what
12 specifically this kind of paper adds. It has some nice
13 features.

14 One of the features is this is a model of
15 spatial price discrimination, so there isn't just a
16 price that the cement plant charges and then people pay
17 transportation costs to the final location. There's a
18 price that the cement plants charge to everybody in a
19 specific county, so instead of having to deal with 14
20 prices, there are 14 cement plants here, they have to
21 deal with 14 times 90.

22 So they have this huge increase in the number
23 of prices that they have to account for in the first
24 order conditions, and there's some fairly large stuff
25 that they have to actually do to actually get this to

1 work, and it's fairly impressive. And I think the
2 reason why it's so much more complicated is so they can
3 deal with spatial price discrimination. So, it would be
4 nice to have more evidence on how spatial price
5 discrimination changes the predictions of the model and
6 how it affects market outcomes.

7 In particular, there's a lot of spatial price
8 discrimination in a lot of markets. Some of the times,
9 you don't realize it because everybody gets charged the
10 same price, but there may be different transportation
11 costs, so that's implicitly spatial price
12 discrimination. We just don't see it that way. So I
13 think it would be nice to emphasize this particular
14 feature of the model.

15 The second feature is for demand and cost
16 estimates, the model is actually getting very
17 reasonable answers, so on the cost side, they find
18 fairly reasonable estimates of transportation costs,
19 which is a nice check that the estimates are doing a
20 good job. Also, in terms of getting aggregate demand
21 elasticity right, they find demand elasticity of .16
22 percent and at the firm level, 5 percent or so.

23 So, we think that cement markets are very
24 inelastic demands at an aggregate level, and they're
25 finding this, and this is to contrast with other work

1 which finds elastic aggregate demand for cement, which
2 just seems wrong. I think this is a nice way of testing
3 that the model is giving reasonable predictions.

4 So going on to the one conceptual thing going
5 on in this model that's maybe controversial but also
6 usual. So, the typical approach in IO is, "Well, let's
7 look at the actual shipments or let's get very micro
8 data to analyze the problem of transportation costs."
9 Often that data is really hard to get, and on top of
10 that, often the moments that you're going to use for
11 estimation, like the average distance traveled might be
12 measured incorrectly.

13 So maybe I'm using the distance just in
14 miles, but sometimes I'm transporting along the
15 highway. Sometimes I'm not. So, it might be
16 mis-measuring transportation distance. So, instead of
17 focusing on micro moments, they're using these
18 aggregate moments, and then consumption in different
19 areas are right. Sometimes we're paying attention to
20 those aggregate moments rather than micro moments, and
21 it might tack down the estimates and give you more
22 reasonable results. So I think there's some value here
23 in being able to do that. This is often the only data
24 that's readily accessible.

25 This method could be used for other cases

1 where we're trying to get the kind of topology of trade
2 costs. For instance, for cement, there's a big
3 difference between water costs and land costs, and for
4 other markets, that kind of difference in
5 transportation costs might be something we are wanton
6 for.

7 I think they have a very rich model and I
8 think they're looking for what the most useful
9 applications of the model are. There are two things
10 that are hard with looking at dynamics for cement. One
11 is we don't see a lot of entry and exit and the second
12 thing is the state's base is huge, so it's the
13 configuration of all the plants in the entire market.
14 And that becomes difficult. So where useful, it's hard
15 to know where to take it.

16 I think instead what this model does better
17 than any other model I've seen is get at spatial price
18 discrimination, and so can we say anything about are
19 there welfare effects of allowing versus not allowing
20 spatial price discrimination? What are the overall
21 effects in this market? And essentially you can do
22 this very easily, and it's not something that
23 empirically you have a lot of evidence on, and for the
24 price discrimination in general, the welfare effects
25 are typically ambiguous of having it or not having it.

1 So it's something we fear is not going to
2 give us a clean answer, and then there's some
3 literature on different forms of spatial price
4 discrimination like basis points on steel that maybe
5 you could also refer to.

6 Then the other issues are also a large role
7 of international competition in this market, but the
8 topology of competition for cement is very weird
9 because it hits coastal markets in a very different way
10 than interior markets.

11 So this model might also have something to
12 say about it. Other people haven't worked on this
13 before. So, I think that would be an interesting way of
14 tying in those trade costs.

15 Thank you. That's it.

16 DR. NEVO: Thank you. Maybe we'll get a
17 chance for the authors, if you want to say one last
18 word or respond to any of the comments? Kate, you
19 expressed an interest. Maybe all three of you can come
20 up here because we might get questions.

21 DR. GENTZKOW: I don't have anything to say
22 other than those are great suggestions. Thank you.

23 DR. HO: I had a couple of things I wanted to
24 say. One is in response to the comment on the last
25 slide. You said you would expect discounts to be lower

1 for high capitation insurers because hospitals are
2 bearing risk.

3 In fact, hospitals aren't bearing risk here.
4 It's the physicians that are bearing risk. Hospitals
5 are bearing no risk, so I didn't think that that was
6 such a counterintuitive finding, so I think that we're
7 okay on that front.

8 You said we need standard errors, we
9 definitely need standard errors. We'll get there. We
10 haven't gotten there yet, and there was a comment at
11 the beginning about whether consumer preferences should
12 be allowed to differ across consumers, across patients,
13 and we do some of that.

14 So we allow preferences for quality to differ
15 across severity groups which is important. We also
16 allow average preferences for quality to differ across
17 insurers, so that we're allowing for selection of
18 different types of consumers into different insurers,
19 for example.

20 What we're not allowing for is for consumer
21 preferences for price to differ across types of
22 insurers. We don't think that's likely as we explained
23 in the paper. We also have a test for that in the
24 inequalities or some kind of a test at least where we
25 estimate the inequalities separately for sick versus

1 less sick patients and find essentially the same price
2 coefficients, but other than that, they were very
3 helpful comments. Thank you.

4 DR. MILLER: I think Allan was right on.
5 Thank you.

6 DR. NEVO: Questions?

7 UNIDENTIFIED SPEAKER: Thanks. This is more
8 an invitation to clarify I hope. Nate, I think near
9 the beginning you said something like you assume that
10 where the data differ from the predictions of the
11 model, it's because of incorrect data measurement.

12 DR. MILLER: That's right.

13 UNIDENTIFIED SPEAKER: If taken out of
14 context or perhaps even if taken in context, that might
15 sound like a rather aggressive assumption. Do you want
16 to clarify what you're really assuming there?

17 DR. MILLER: Do you mean that it might be
18 data due to incorrect specification? So in general
19 once you aggregate out the predictions of the model and
20 compare that to the data, they're not going to be
21 exactly right, and one needs to talk about what that
22 error is and how to deal with it.

23 I guess if you're willing to say the error is
24 endogenous to the plant locations and to the cost and
25 demand shifters, and the error here being the

1 discrepancy between the predictions and the data, then
2 you get the nonlinear multiple equations, nonlinear
3 least squares.

4 If there's some relationship between that
5 error and the plant locations, which I kind of scratch
6 my head on why that might be the case, but if it
7 happened, what one would need to do is instrument, and
8 you would get a slightly more complicated estimator,
9 but I think estimation would still be feasible.

10 Essentially what one would need is an
11 instrument that is correlated with the equilibrium
12 predictions, that's not correlated with whatever the
13 term would be. You would have to think hard about that
14 what actually is in the near term.

15 DR. NEVO: Other questions?

16 UNIDENTIFIED SPEAKER: I have a question for
17 Kate. We heard this morning from Roman Inderst about
18 some of the agency problems that exist with financial
19 advising. It would seem that the introduction of any
20 incentives to get doctors to make decisions which are
21 lowering costs and maybe in the interest of the HMO or
22 whatever is likely to be -- well, I guess I worry about
23 that that introduces an agency problem with the
24 patients.

25 You started out the paper, motivating it by

1 saying we're looking for ways to reduce costs without
2 reducing quality, and somehow that seems to me to be
3 impossible to be able to do, and then I worry about
4 this potentially agency problem and should there be
5 some transparency? Should patients be aware that their
6 doctors have these capitation things going on? And is
7 there anything in the work that you've done that would
8 speak to that?

9 DR. HO: That's a great question, and it's
10 something we haven't looked at in detail so far. We've
11 looked at women going into the hospital to give birth,
12 and in some sense we're less worried about quality
13 there, the quality of the hospital they're going to
14 than we might be if these were patients with cancer or
15 some more severe illness. We have plans in the works
16 to try to understand the trade off being made here
17 between quality and price.

18 So far we're just looking at whether price
19 matters and the extent to which it matters. There's
20 obviously a follow-up question about how much are we
21 losing in terms of quality.

22 From the initial analysis we've done, it
23 actually looks as if patients are going to cheaper
24 hospitals. They're cheaper because for reasons that
25 might not be related to quality. They're cheaper

1 because they're hospitals that aren't very high tech.
2 They don't offer transplants, for example. Women
3 giving birth don't care if the hospital offers
4 transplants or not.

5 It's not about the number of nurses in the
6 hospital. It's not about C section rates, so our
7 initial analysis is saying quality isn't suffering to a
8 large degree, but I agree that there's a lot we could
9 look at there that we haven't done.

10 UNIDENTIFIED SPEAKER: Thank you. My
11 question is for Matt in the first paper. I tend to
12 think about the extensive preferences, but even I was
13 surprised by this drop of 60 percent once you moved, so
14 I was wondering what would be the explanation for that?
15 And maybe it's just a question, I don't know how you're
16 measuring migration of the household because if only
17 one part of the household, one member of the household
18 migrated, you might explain the -- if 60 percent of
19 people came from California to marry a woman in
20 Washington, you might expect a jump in broad terms.

21 So I wonder if you can differentiate if the
22 whole household moved or only one part of the
23 household.

24 DR. GENTZKOW: Good question. In response to
25 the second part, we actually have data at the

1 individual level within household. We had individuals
2 fill out the survey. In the large share of households
3 if there are multiple people, they both filled it out.
4 We did something pretty simple with that where we just
5 select whoever does most of the shopping and used them.

6 In the panel, household composition is
7 remaining constant over that time so I think it's not
8 an issue. In terms of what explains the jump, which I
9 think is really an interesting question, we have some
10 descriptive evidence in the paper, prices. This you
11 really could have really expected might go either way,
12 but prices are lower where brand shares are high.

13 So when you move from a state where Folgers
14 is popular to a state where Maxwell House is popular,
15 you're getting lower price for Maxwell House. That's
16 one obvious thing that would explain an immediate
17 change.

18 Second, something that's harder to measure
19 but that I think intuitively we think all of the
20 literature on how stores allocate shelf space says to a
21 first approximation, they should do that proportional
22 to market shares, so you move to somewhere where
23 Maxwell House is popular and if you are the kind of
24 person who just walks into the store and picks whatever
25 is there, you're going to immediately start buying more

1 Maxwell House.

2 Advertising and promotional activity are also
3 positively correlated with this. We can kind of do a
4 decomposition exercise in terms of the covariances.
5 How important those different things are, we can't
6 really separate them, but I think the behavior is
7 consistent with that, and we're doing some follow-up
8 work thinking about the supply side and what explains
9 how firms' decisions will be different in a place where
10 those things are higher.

11 Those supply side variables are what make
12 this persistent over long periods of time because it
13 means if the old people in this place like Maxwell
14 House, if that makes it optimal for me to charge lower
15 prices and have more variability, then new consumers
16 coming into the market will learn to like Maxwell House
17 as well and it's going to persist over generations.

18 DR. NEVO: Are we done in terms of time?
19 Well, let's all thank the speakers and discussants.

20 (Whereupon, a brief recess was taken.)

21 DR. ADAMS: We have lunch out on the tables,
22 and I should say that our calorie information is
23 exactly the same as our price information. Please come
24 back here at about ten past 1:00. Feel free to bring
25 your sandwiches back in but not your conversation.

1 (Whereupon, at 12:40 p.m., a lunch recess was
2 taken.) AFTERNOON SESSION (1:10 p.m.)

3 DR. BECKER: I'm going to make a quick
4 announcement as people are filing in. We've made a
5 change in how we are doing wireless in this room, so if
6 you would like wireless access here, you need to go out
7 to the table in the front where you first signed in.
8 There's a list. You can put your name on the list.
9 There's also someone out there so you can ask them if
10 there's any confusion about it.

11 It's an honor for me to introduce an
12 economist who has been incredibly influential in both
13 how we do things at the FTC or how we do things in
14 Consumer Protection, but also how economists everywhere
15 think about economic decision making.

16 David Laibson is the professor of economics
17 at Harvard University. He's advanced economics by
18 looking inside the black box in a lot of areas
19 including intertemporal tradeoffs and decision making
20 under limited information.

21 His research has been published extensively
22 both in economics journals such as the AER and QJE, but
23 also in journals outside of economics such as Science
24 and the Journal of Neuroscience.

25 His contributions have been so extensive that

1 I feel he deserves a long introduction, but I'm going
2 to turn the floor over to David Laibson.

3 (Applause.)

4 DR. LAIBSON: Thanks a lot for this
5 opportunity and the invitation. It's great to be here.
6 I want to tell you about some work with Sumit Agarwal,
7 who is at the Fed in Chicago, John Driscoll, who is at
8 the Fed here, and Xavier Gabaix who is at NYU. And as
9 you probably all know, this is not in any way
10 reflective of the views of the Fed.

11 So this is a talk about financial decision
12 making over the life cycle, and it's just a motivating
13 example. Considered Brooke Astor. This is shortly
14 after her wedding to the Astor family at age 51, and
15 you know the story of her life cycle.

16 She, for the next 50 years after that,
17 becomes the leading member of society in New York City,
18 the major advocate for almost every charity in New York
19 City. She eventually receives the highest civilian
20 honor available in this country, the Presidential Metal
21 of Freedom.

22 Shortly thereafter she begins to decline
23 cognitively, eventually gets an Alzheimer's diagnosis,
24 and is then the victim of psychological and physical
25 abuse from her son. Eventually he's convicted of grand

1 larceny and is now in jail. She died around 2006, I
2 think. I'll be talking about maybe less extreme
3 examples of those kinds of sad endings.

4 So there are a lots of performance peaks
5 wherever you look in economic life and in life more
6 generally. Here are a few examples. You want to find a
7 good dictator. He or she should be about 45. You want
8 to find a good economist. There's debate actually on
9 what the right age is for great economic research is.
10 I want to go into that.

11 Today we're going to talk about financial
12 performance, how people make financial decisions in the
13 domain of credit card markets or in the area of credit
14 markets, and I'll talk about performance in ten
15 different areas. We'll basically find that performance
16 rises and declines with age in the cross-section and
17 we'll be measuring performance based on fees and
18 negotiated interest rates in loans.

19 So, these are the markets that we studied.
20 I'm going to go through them one at a time later, but
21 we basically got data from a bank that shared with us
22 every bit of information they had in all of these
23 markets, and we'll show you what we learned. We had
24 all the data that they had on their borrowers.

25 Now, when we talk about this pattern of

1 rising performance and then falling performance, there
2 are obviously many stories that might come to mind.
3 That pattern was observed in this data, primarily in
4 the cross-section. So, when we talk about reduction
5 effects or current effects perhaps driving that
6 pattern, and I'll talk quickly about why we think
7 that's not what's going on here.

8 There's a large and, I guess, small but
9 rapidly growing literature beginning to think about how
10 cognitive performance affects economic decision making
11 in the domain of age. I think some of the key
12 contributors are Korniotis and Kumar and Zinman, who is
13 here today. There's a lot of literature thinking about
14 how differences in cognitive capabilities affect
15 important economic outcomes.

16 So I will present ten different credit
17 markets and talk about behaviors in those markets and
18 then to discuss quickly the various explanations, and
19 I'll emphasize age related effects as opposed to overt
20 effects or selection effects.

21 This is the first set of markets we want to
22 talk about. It's loans collateralized by a home, so
23 we'll be talking about home equity loans and home
24 equity credit lines. This is again proprietary data
25 from a single bank, and everything that I show you

1 comes from the same bank who wishes to remain
2 anonymous.

3 The data for homes involves 75,000 contracts,
4 and these are contracts from 2002. Again we observed
5 everything the bank observes, and we're going to put
6 all those data, all those characteristics on the
7 right-hand side of these equations. The key variable
8 that we will studying on is the age line which will go
9 on the right-hand side of the equation.

10 So let's take a look at how interest rates,
11 home equity lines vary with the borrower's age,
12 controlling for every bit of information that the bank
13 has about the borrower and keeping in mind that banks
14 can't make age contingent interest rates. That would
15 be illegal. Here's what we see in the data.

16 You can see this U-shaped pattern. If you're
17 a young borrower, you're going to pay, in this, example
18 about 6.4 percent. If you're a middle age borrower,
19 you're going to pay 5.4 percent, and if you're an older
20 borrower, here going up to age 80, you're going to pay
21 about 6 percent.

22 There are no standard errors in any slide I'm
23 going to show you because they're all tiny, so tiny
24 that you just see little parallel lines walking this
25 thing down and up because we have so much data.

1 Here's the same plot now for home equity
2 credit lines, and we see basically the same pattern
3 here as well. We see a hundred basis point improvement
4 as we go from young to middle age, and then a 75 basis
5 point worsening as we go from middle aged to age 80.
6 I'm going to keep moving. We're going to see ten
7 markets in total.

8 In the next market, this is what we call
9 reactive behavior. Back in the day before the Fed
10 banned it not so long ago, credit card companies
11 engaged in the following routine: They would say to a
12 new client, "Please transfer balances from your old
13 credit card company to this new credit card company,
14 us," and the big letters would say, "And you're going
15 to get a low interest rate on the transferred
16 balances."

17 Then the fine print would say that every time
18 you make a payment on the new card, we'll be crediting
19 your balance transfer first before crediting the actual
20 new charge, which means that as you make new charges,
21 you're accumulating high interest rate debt and
22 effectively with each payment paying off the low
23 interest rate debt.

24 By implication the optimal strategy is to do
25 the balance transfer and then put the card in a desk

1 drawer and forget about it until the low interest rate
2 period expires. Not using the card is the only way to
3 take maximal advantage of the transferred balances at a
4 low interest rate.

5 Now, that's pretty hard to understand. I
6 didn't get it the first ten times I read these
7 inducements back eight or nine years ago when they were
8 popular. Let's see who gets it in terms of the people
9 who are actually taking up these offers.

10 So take a look first at the light blue
11 greenish line. So it's like a blueish, greenish,
12 grayish line. And what that's plotting is the fraction
13 of individuals who get one of these balance transfer
14 offers and don't get it because they keep using the
15 balance transfer card to make new charges, basically
16 effectively losing the ability to fully take advantage
17 of the balance transfer.

18 You can see that a lot of the older
19 individuals who are bucketing over 65, over half of
20 them, don't ever get it, meaning they keep using the
21 card for the entire duration of the low interest
22 period. Among middle aged borrowers, only 25 percent
23 never get it, and among young borrowers, 45 percent
24 never get it.

25 And the opposite of that are those that get

1 it right from day one and never use the card -- I'm
2 actually amazed at how many people fall into this
3 category; they're far brighter than I am -- 25 percent
4 get it from day one and don't use the card in the
5 youngest age bucket. 45 percent get it from day one and
6 don't use the card in the middle age bucket and about
7 20 percent get it from day one and don't use the card
8 from the oldest aged bucket.

9 Now, I'm going to go through seven more
10 categories of credit card or credit market behavior.
11 We'll talk about fees and then we'll talk about a bunch
12 of interest rates.

13 So first fees: You can see here the
14 frequency of late payment fees, the dashed blue line up
15 here, the frequency of cash advance fees. This is a
16 monthly basis and the frequency of over limit fees down
17 here, and again you see the same U-shaped pattern,
18 though the magnitudes now are less pronounced since the
19 scale is somewhat compressed.

20 Here we see auto loan interest rates and
21 again we're on the right-hand side controlling for
22 everything that the bank sees. You can see here the
23 same U-shaped pattern, though a bit less pronounced.
24 Now the differences here are from 9 percent down to
25 about 8.7 percent, 30 basis points, and then maybe 20

1 basis points back up on the other side.

2 Here are credit card APRs by borrower age. We
3 see a robust decline in the beginning of life and then
4 a nature or slightly rising pattern later in life.
5 Here are mortgage APRs by borrower age. Here again you
6 see a decline and rising later in life. This is about
7 40 basis points different here. Here you see small
8 business credit card APRs, again the same U-shaped
9 pattern.

10 Now, if you take all that data, and you push
11 it all together and you ask, "Where are individuals
12 getting the best deals, paying the lowest risk adjusted
13 interest rates or FICA adjusted interest rates?" It
14 turns out it's about age 53. We estimate that by taking
15 the middle aged population and fitting a quadratic to
16 that population, so it looks like the peak of financial
17 performance, those who are doing best in the data, are
18 53 years old or thereabouts.

19 There are a lot of explanations that are
20 plausible candidates for this pattern. I want to focus
21 on the age related effects and then try to talk you out
22 of selection effects and cohort effects.

23 Let's begin with age related effects. We'll
24 begin with little background. There are basically two
25 kinds of intelligence that we humans seem to have. At

1 least psychologists bucket it this way. There's
2 crystallized intelligence, and there's fluid
3 intelligence. Crystallized intelligence is the name of
4 the vice president. Is that a hard one? Believe it or
5 not, that is a hard one for many Americans.

6 Fluid intelligence is your ability to see a
7 new problem and solve it, so crystallized means a
8 familiar piece of information. You've heard it before.
9 Can you basically recall it? Fluid intelligence is
10 your ability to confront a brand new problem and get it
11 right, so let's take a look at fluid intelligence
12 tests.

13 This is the bad news, so I'm about to give
14 you some awful news, which I hope you'll accept rather
15 than deny. These are tests for fluid intelligence.
16 Here's a memory test. Here's a list of ten words,
17 which of them can you remember and then write down
18 after the list disappears? Here's a spatial
19 visualization test. Look at this two-dimensional
20 object on the left, cut it in your mind away from the
21 background paper, fold it accordingly, and which object
22 on the right will you have reproduced?

23 Here's a matrix reasoning. That's right,
24 it's not so easy. Here's a matrix reasoning task:
25 Which is the missing object in the lower right-hand

1 box. And then finally perceptual speed, take a look at
2 those two objects in each row and very quickly tell me
3 whether they're the same or different.

4 So these are examples of the kinds of tests
5 that are used to measure fluid intelligence.

6 Now, unfortunately in the cross-section, this
7 performance declines very, very sharply over the life
8 course, so if you look at 20 year olds on fluid
9 intelligence, this is on any measure, perceptual speed,
10 20 year olds perform at about the 73rd percentile of
11 the adult population while the average 80 year old
12 performs at about the 16th percentile of the adult
13 population.

14 Here's data from the HRS, which is not in a
15 cross-section. This is data that we're actually
16 controlling for fixed effects because people are given
17 the same questions repeatedly. And you can see here,
18 for example the answer to the question, if the chance
19 of getting a disease is 10 percent, how many people out
20 of 1,000 would be expected to get the disease.

21 A fraction of people who answer a hundred; 80
22 percent at age 50, not so great; 50 percent at age 90,
23 not so great, too. Here's another question. Can you
24 divide two million by five to get the answer 400,000?
25 At age 50, about 50 percent can do that. At age 90,

1 about 10 percent can do that.

2 Now, part of the story is dementia, more bad
3 news. Basically the prevalence of dementia doubles
4 every five years with age, so it goes from .8 to 1.7 to
5 3.3 to 6.5 to 12.8 to 30.1. Every five years of your
6 age, your likelihood of having dementia doubles.

7 Moreover, there's the risk of not quite
8 having dementia, but being on the door stop of dementia
9 because you're cognitively impaired but you're a few
10 years away from a full-blown dementia diagnosis. It
11 turns out in the 70s, that's about 16 percent of the
12 population. In the 80s, it's about 29 percent of the
13 population, and in the 90s, it's about 39 percent of
14 the population.

15 Put this together and you will see that
16 approximately half of adults between age 80 and 90
17 either have cognitive impairment, just short of
18 dementia or full-blown dementia, half the adult
19 population in that age band.

20 So what is average dementia rating between
21 age 80 and 90? It's about a diagnosis halfway between
22 mild dementia and moderate dementia. So put all this
23 together; what do we see? We see a pattern whereby
24 crystallized intelligence, people's ability to remember
25 that the vice president is Biden, is basically rising

1 dramatically over the life course as they gain more
2 experience, but fluid intelligence, the ability to
3 solve a new problem is rapidly declining over the life
4 course.

5 If you think about our decisions as being in
6 some sense a composite of experience and fluid
7 intelligence, it's not really surprising that's going
8 to rise and then fall over the life course, so
9 performance would be peaking around mid age.

10 One test of the hypothesis is to ask how
11 performance changes as people enter different
12 activities at different points in life. And the
13 prediction would be that when you enter an activity,
14 there's a period of rising performance, as you gain
15 experience. That's that concave, crystallized
16 intelligence function, being hit by declining fluid
17 intelligence as you get older and older.

18 So you would expect performance peaks to
19 occur later, and later the later in life one begins a
20 new activity. That's exactly what we see when we look
21 across the ten domains of behavior that we've been
22 studying. Performance peaks are later as people begin
23 some activity later in life.

24 Now, another possible explanation for all of
25 this is a cohort effect or a selection effect. Let me

1 first turn to selection effect. So there are two kinds
2 of selection that we're able to rule out. One kind of
3 selection is that individuals who are in our sample are
4 unrepresentative of the full population at those
5 different ages, so perhaps the young people in our
6 sample, because we're dealing with again selected
7 individuals in the database of this large bank. And
8 maybe the old people in our sample are not
9 representative of typical young and old people in terms
10 of education and other characteristics.

11 We can go to the SCF and ask whether debt
12 holders are more or less sophisticated across the age
13 range and in fact this works just the opposite way.
14 Young debt holders and old debt holders are in fact
15 more sophisticated than the average individual based on
16 education and income in those age buckets. So, the
17 first selection effect actually goes against us. It's
18 not pushing results in our direction.

19 The second effect is that perhaps middle aged
20 borrowers are just different, less risky than the young
21 and old that borrow. There again, the evidence points
22 in exactly the opposite direction. If you look at the
23 data that we have, the middle aged borrowers are in
24 fact the most likely to default and the old borrowers
25 and the young borrowers are in fact the least likely to

1 default, so none of those results are explained by the
2 default rates or the risk characteristics of those in
3 middle age.

4 We don't think cohort effects are driving the
5 data for many, many, many reasons, but the most
6 important is the last one on the slide which is when we
7 go back in time to data ten years earlier, we see the
8 exact same pattern of performance peaking at age 53.

9 If it were a cohort effect, we would expect
10 to see that peak shifting as they allow the sampling
11 for the cross-section, but we don't see that shift. We
12 see the peak of performance at 53 staying in the same
13 location regardless of the time period in which the
14 cross-section is sampled, so that seems to rule out
15 cohort effects.

16 Now, there's cost of the time effects, but
17 they go in exactly the opposite direction. If you
18 think that it's the cost of time that's varying over
19 the life course, you would expect that older adults who
20 are retired and have lots of time would be making the
21 best decisions and young adults who were presumably not
22 facing a lot of time demands because they have low
23 wages and small families would also be making good
24 decisions, but that's not what we see.

25 It's the middle aged that make the best

1 decisions, despite the fact that they have the most
2 demands on their time and the highest opportunity cost
3 of time, so we don't think that the cost of time can
4 even plausibly explain any of these effects. As I
5 mentioned before, it's not default behavior since the
6 default rates in our sample of prime borrowers are
7 highest for the middle aged and lowest for the young
8 and the old.

9 So to conclude, we see a robust pattern of
10 low performance for the young and the old relative to
11 high performance for the middle aged across all the
12 markets for which we have data. There are others who
13 have also looked at their data and found similar
14 patterns.

15 I believe Fiona did that at some point. And
16 there are several other collaborative teams who have
17 been looking at their own data control. And they're
18 seeing the similar pattern that when you control for
19 the characteristics that are relevant, say FICA scores,
20 say loan to value ratios, you find that the middle aged
21 are performing better on economic tasks than the young
22 and the old.

23 Now, I want to emphasize one policy issue
24 before finally concluding. The paper that I'm
25 discussing here actually contains a large range of

1 policy observations, but I don't have enough time for
2 that today. We actually have a remarkably perverse
3 regulatory framework, vis-a-vis financial decision
4 making in this country.

5 We have an excellent regulatory safety net
6 for middle aged people in the form of pension plans
7 that are regulated by ERISA, and then because of that
8 regulation an investment committee that acts as a
9 fiduciary that screens out bad choices, that basically
10 creates an incredibly safe sandbox for employees
11 between age 20 and retirement, 65.

12 Then after you retire, you exit your
13 retirement savings plan. You exit your pension plan,
14 and you end up in an IRA rollover that has no fiduciary
15 protection, that has absolutely nothing that is even
16 approximate to ERISA. It's basically a Wild West, so
17 we've completely reversed the appropriate regulatory
18 environment.

19 Instead of providing regulation that really
20 protects vulnerable older adults with large chunks of
21 retirement wealth, we have built a system that protects
22 the middle aged, according to our results, those who
23 need it the least.

24 Let me summarize. Older adults experience
25 substantial declines in analytic cognitive function,

1 declines that, I think, we should be very worried about
2 as regulators. And certainly we should be thinking
3 about as economists because that can lead to all sorts
4 of interesting economic behavior that doesn't jive with
5 the rational actor model. The data we've looked at
6 today, data from credit markets indicates that the
7 middle aged appear to be doing relatively well on every
8 dimension that we were able to study relative to the
9 young and the old.

10 There are a lot of open questions. This is
11 just, I think, I hope, the beginning of a research
12 program to come covering questions like how important
13 are these losses, questions like to what extent do
14 individuals anticipate these changes in their cognition
15 as they approach retirement and prepare for them.

16 There's lot of things you can do: irrevocable
17 trust, bringing powers of attorney. Are individuals
18 able to avoid these problems by creating institutional
19 protections for themselves either with the help of the
20 government or just on their own with the help of some
21 kind of legal intervention?

22 Does financial education help? Do third
23 parties help? Can we delegate successfully these
24 decisions or are we stumped at making them ourselves
25 and thereby making them badly? How is the market

1 responding to this? Is the market creating a solution
2 or is the market evolving to exploit these vulnerable
3 older adults and creating opportunities to separate
4 them from their money?

5 Then finally: What is the appropriate
6 regulatory response? I believe at the very least we
7 should level the playing field and give older adults
8 the same protections that we've been offering middle
9 aged adults to date.

10 Thank you.

11 (Applause.)

12 DR. LAIBSON: So I don't know whether we want
13 to take questions now? I am happy to, but I understand
14 if you want to get back on schedule.

15 DR. ROTHSTEIN: We can take questions for
16 five minutes.

17 DR. SCOTT MORTON: Fiona Scott Morton. I
18 just want to ask a question. You said you put
19 everything that the bank knows on the right-hand side.
20 Why then is there a residual? What is that residual?

21 DR. LAIBSON: With regard to interest rates,
22 I go into a bank and I negotiate for an interest rate.

23 Now, it's true if I'm just reading off a
24 schedule of interest rates, there's no residual, but
25 that's not the way it works. There are all sorts of

1 steps in which I can end up going off the standard
2 schedule and ending up asking for a better rate,
3 walking out if I can't get that rate, et cetera.

4 We think that's the key element, and we
5 actually have evidence of where the negotiation is
6 breaking down. It turns out that the middle aged have a
7 much better understanding of the value of their homes
8 than do the young and old. So when you come into the
9 negotiation with a very poor understanding of the value
10 of your home that gives the bank an opportunity to
11 deviate from the standard routine and offer an interest
12 rate that is basically punitive.

13 That's the case at this bank; we spoke to the
14 origination group, and that's the way it works.

15 UNIDENTIFIED SPEAKER: David, I'm sure you
16 thought of this: Is income an alternative explanation
17 here? The greater your income is, the more flexibility
18 you have to be able to take advantage of the optimal
19 things that come along or the less constrained you are
20 to be able to make better choices and income peaks
21 around 53 as well?

22 DR. LAIBSON: For most of these data sets, we
23 have income, so that is an argument on the right-hand
24 side. So, I don't think that would be it, though I
25 guess it's one issue that I thought of as you were

1 asking the question. We have probably linear and log
2 income on the right-hand side and maybe there's some
3 interesting alternative function that might be better
4 at soaking up some of that variation but we do have log
5 income on the right-hand side.

6 DR. GENTZKOW: You sort of dodge the question
7 of magnitudes here by saying that's an open question.
8 It seems like there's a lot of direct stuff in your
9 data about how big these things are and many of them
10 look small kind of eyeballing interest rates, but what
11 do you know about the size?

12 DR. LAIBSON: So we think the effects are
13 going to be absolutely enormous when you add them up
14 across every single domain. If you're going domain by
15 domain and you ask how much more interest are people
16 paying at age 85 on their credit cards? A couple
17 hundred bucks a year, but you then think about the
18 credit card and the mortgage and the low returns on
19 their financial products.

20 So Korniotis and Kumar estimate a 200 basis
21 point lower risk adjusted return for 80 years old
22 relative to people in the middle age, and that's a
23 terrifying number. If it's 200 basis points and that's
24 your retirement wealth and you're talking about let's
25 say a \$500,000 pool of assets for an upper middle class

1 family, that would be, I believe, \$10,000 a year in
2 differential returns, presumably just as a function of
3 your age.

4 That's not even taking into account things
5 like fraud, so there's this enormous concern now in
6 Washington that there's a huge set of market actors
7 targeting these individuals and stripping them of their
8 wealth in ways that are borderline legal. And that's
9 another huge category of losses, so no one's added it
10 all up, but if we think if one did add it all up, it
11 could be that you're stripping from a typical 80 year
12 old \$5,000 to \$20,000 a year by the time you've taken
13 all the categories and strung them together.

14 DR. GENTZKOW: It would be useful to know
15 those.

16 DR. LAIBSON: Yes, and we do have those
17 numbers in the paper. Within the domain, you're right.
18 It's on the order of \$500 a year within this domain.

19 UNIDENTIFIED SPEAKER: So given that the
20 bank's data may not perfectly capture liquidity
21 constraints or the consumers expected near term or
22 medium term liquidity constraints, have you thought
23 about whether you might be just picking up something
24 about the life cycle of credit demand on the loan
25 pricing stuff?

1 Is the early 50s the age at which liquidity
2 constraints bottom out because kids are leaving the
3 house and you're not getting hit with uninsured medical
4 expenses yet and so on and so forth, and so maybe this
5 is sort of where demand for credit bottoms out, so
6 people bargain hard, and if they don't get the deal
7 they want, they walk away?

8 DR. LAIBSON: Well, I'm skeptical about that
9 story for two reasons. The first is that if it were
10 the kind of life cycle of liquidity needs, we usually
11 think about liquidity needs being the lowest just
12 before retirement, when you have this big pool of
13 assets that you've saved up for retirement, whereas we
14 think about household and the 50s as still in the
15 process of paying college tuition and stuff like that.

16 So I would have thought that the liquidity
17 story would have generated the best rates for 64 year
18 olds who have the big pool of assets. But the other
19 thing that makes me think it's not liquidity is that we
20 have got a lot of characteristics on the right-hand
21 side that are basically measures of the financial
22 desperation of the household, like FICA scores and like
23 loan to value ratios.

24 So again in some sense those controls are in
25 there, though they're imperfect.

1 UNIDENTIFIED SPEAKER: I don't know whether
2 this is in the data you have, but if we think that part
3 of it might be different bargaining behavior, it would
4 be interesting to know what fraction, by age of initial
5 negotiations, do not lead to a final transaction.

6 DR. LAIBSON: We don't have that data and I
7 should emphasize that would be great data to get. It's
8 not in our data set. We wanted that and couldn't get
9 it out of the bank. When I say negotiation, I actually
10 mean two things that fall under that category.

11 The first is getting a bank to give you a
12 better offer, and the second is walking out the door
13 when the bank gives you a bad offer. So, you could
14 think about some people just coming in and getting
15 something that's inflexible and taking it, whereas the
16 smart folks say, "That's not a competitive offer, I'm
17 out of here." I think both of those margins are active
18 in terms of this negotiate premium.

19 UNIDENTIFIED SPEAKER: It's fascinating data
20 and I think it really speaks to our concerns in
21 consumer protection about basically which groups of
22 consumers we have to protect, the very young ones and
23 the very old ones.

24 We see it in many different markets as well,
25 but now you have started talking a lot about social

1 interactions which may explain some of the outcomes,
2 the negotiations, and actually you say here you have
3 data, but then you tell a story.

4 The story you basically tell is one of
5 cognitive ability and knowledge. Maybe some of your
6 findings can also tell a different story, and it's a
7 story that's told in other markets. For instance, in
8 your case, Office of Fair Trading has done a study of
9 doorstep selling.

10 They found obviously that for those consumer
11 groups which are particularly vulnerable, particularly
12 the very old ones, their story was not one of cognitive
13 abilities, but one of social inference, for instance,
14 like which kind of people are not giving into pressure,
15 which kind of people are basically falling in my topic
16 advice and recommendations. And from this perspective,
17 I think you can also tell a story that would explain
18 some of your data.

19 From some regressions I've been running, we
20 have seen that those were not naive with respect to
21 advice. It seems to be those which are not in a
22 business situation at the moment, for the young ones
23 and the very old ones, whereas those say you are 40, 50
24 years old, these people may think about each and every
25 transaction from a business oriented sense, so maybe

1 that can also explain it.

2 That's like different concepts like
3 reasoning. These may basically think about these
4 decisions when they make them together with the bank
5 official, like a social interaction flavored with a cup
6 of coffee. Whereas the 40 or 50 years old will think of
7 business savvy, so maybe that can also explain it. But
8 the nice thing you have in here are different
9 decisions, those which are taken alone and those that
10 are taken in the social context. Maybe you could try
11 to do more on this.

12 DR. LAIBSON: So that would explain some of
13 our settings, but as you just anticipated I think in
14 the last sentence, some of our settings are completely
15 private settings, meaning there's no one on the other
16 side of the decision, for example, the eureka moments.
17 And I think the fact that we see the robust pattern
18 across all the settings, those that have a social
19 possible interpretation and those that don't, makes me
20 think that while the social story is plausible, it can
21 only be part of the story.

22 Thank you very much.

23 (Applause.)

24

25 PAPER SESSION TWO: INATTENTIVE CONSUMERS

1 DAVID LAIBSON, Chairman, Harvard University

2 PRESENTER: MICHAEL GRUBB, Massachusetts Institute of
3 Technology, Sloan School of Management

4 DISCUSSANT: Ginger Jin, University of Maryland

5 PRESENTER: JONATHAN ZINMAN, Dartmouth College

6 DISCUSSANT: Karen Pence, Federal Reserve Board

7 PRESENTER: NICOLA LACETERA, University of Toronto

8 DISCUSSANT: Kory Kroft, Yale School of Management

9 DR. LAIBSON: I'm now going to run this
10 session, but I'm not going to sit there because I want
11 to be able to see what's going on. So we've got three
12 terrific papers and the organizing principle for this
13 session which kind of emerged by accident is
14 inattentive consumers. All the papers speak to that
15 issue, and our first presenter is Michael Grubb from
16 MIT.

17 DR. GRUBB: So thank you very much for having
18 me. I'm going to talk about penalty pricing and
19 regulation requiring firms to disclose at the point of
20 sale whether penalty fees might apply on that
21 transaction.

22 The motivation for this research comes from
23 three observations. The first is that there's a lot of
24 situations where services are priced non linearly for
25 which a consumer may be fully aware of the contract

1 terms and yet unaware of what the marginal price of any
2 particular transaction is.

3 So, for example, imagine a cellular phone
4 customer. They're fully aware that their contract
5 marginal price of minutes is zero up to their 500
6 minute allowance. Thereafter, it's 35 cents a minute,
7 but if they haven't kept track of how much they've
8 talked on the phone or it's a family plan and they
9 haven't heard from their spouse how much their spouse
10 used, they don't know whether or not they're over that
11 500 minute limit. And then the phone rings, they don't
12 know whether the marginal price is zero or 35 cents a
13 minute.

14 Similarly, a bank customer might be fully
15 aware that a debit card swipe transaction has a zero
16 transaction fee. If there's no money in their account,
17 the fee is a \$35 overdraft charge. And yet, if they
18 haven't kept track of how much money they're spending,
19 they might not know whether there's money in their
20 account, and therefore not be sure whether the next
21 transaction fee is zero or \$35.

22 There's growing empirical evidence showing
23 that people are in fact uncertain about whether these
24 penalty fees apply at the point of sale. We're going
25 to hear some very interesting stuff on that from Jon

1 Zinman next.

2 The second point is that this unawareness of
3 the marginal price and point of sale is endogenous so
4 firms have the option to could make your phone screen
5 flash bright red and say, "Overage fee applies" when
6 the phone rings to let you know before you answer.
7 They don't. You can go online and find out how many
8 minutes you've used or call a number, but it's not put
9 right in front of your face.

10 Similarly, you can check your checking
11 account balance online or do a balance inquiry at the
12 ATM, but when you swipe at Starbucks for your coffee,
13 it won't say that an overdraft fee is about to apply
14 and ask if you would like to continue.

15 So my question is: What would be the effect
16 of requiring firms to make this disclosure of whether
17 or not a penalty fee applies to that transaction and
18 would it be a good idea?

19 Related to the second point - and this may
20 not be news to people here -- there's been some recent
21 regulatory attention on this issue. So for example, for
22 these particular two applications of cell phone charges
23 and overdraft fees (We'll hear a lot more about the
24 overdraft fees in a minute.) since July, the Fed is
25 requiring banks to actually ask customers in advance if

1 they would like the overdraft protection service.

2 With respect to cell phone charges, there's
3 recently been a bill shock regulation in the EU, and
4 the FCC is considering something similar here, which
5 would require firms to send a text message to consumers
6 if they start triggering these high fees, and their
7 bill starts increasing, so that's the motivation.

8 What I'm going to try to do, if I can manage
9 it in the 20 minutes, is first talk about how consumers
10 make choices, at least as I model it, when they're
11 unaware of the price. Essentially the answer is going
12 to be they're going to respond to an expected marginal
13 price rather than what it actually is, and then I'm
14 going to go through three models.

15 The first model is a benchmark model where
16 everything is as simple as possible. There the main
17 result is an equivalence result. Essentially it says
18 that I'm thinking of two different types of consumers,
19 ones who keep track of your usage -- I am calling
20 those attentive consumers -- and ones who don't keep
21 track of their usage, so unaware of whether or not a
22 penalty fee applies. I'm calling those inattentive
23 consumers.

24 The first result is it doesn't matter whether
25 consumers are attentive or inattentive, and if they're

1 inattentive, it doesn't matter whether or not we
2 require firms to disclose information about the price
3 then. Profits, market shares, consumer surplus,
4 allocations are all going to be unaffected. The only
5 thing that might differ is actually the prices we
6 observe.

7 The second model I'm going to talk about
8 enriches things in a way where I think is particularly
9 applicable to the seller of phone context.

10 So, companies don't just offer one contract;
11 they offer a menu of contracts. Why is that? Because
12 consumers are different. Some expect to talk a lot on
13 the phone. They might buy a plan with a high monthly
14 fee, but a lot of included minutes. Others expect to
15 talk very little on the phone and pick a cheaper plan.

16 I want to introduce this sort of
17 heterogeneity into the model, and there's a model for
18 price discrimination. Now I find that the issues of
19 inattention and disclosure actually matter a lot.

20 One of the things I find is that now it
21 definitely makes sense for firms to charge penalty fees
22 and to make them surprise fees. And so endogenously for
23 them to decide not to disclose at the point of sale
24 whether a penalty fee applies, but interestingly,
25 regulation requiring them to do so can be

1 counterproductive, and will be counterproductive, if
2 you believe all the assumptions in the model, in fairly
3 competitive markets.

4 Now, I think this might apply to the cell
5 phone pricing and so you should be cautious about this
6 new FCC bill shock regulation. I think it doesn't
7 apply as well to the bank overdraft charges case
8 because although banks offer different types of
9 checking accounts with different terms and fees and
10 tries to sort different target customer groups into
11 those different accounts, as far as I'm aware, in the
12 past they haven't used the overdraft fees to help in
13 that sorting. The overdraft fee structures have been
14 similar across all the types of accounts.

15 So, this price discrimination doesn't really
16 apply. I have a third model that I think may be
17 insightful to the overdraft fee case. My assumption
18 here is that consumers might underestimate their demand
19 for the service, in this case essentially underestimate
20 how much they're spending, and so underestimate the
21 likelihood of going below a zero balance and triggering
22 overdraft fees.

23 There again I find that it makes sense for
24 firms to charge penalty fees and not tell consumers at
25 the point of sale that they're about to apply. Here I

1 don't have clear conclusions about whether price
2 posting regulation would be good or bad for welfare.
3 It could go either way, but I think there's potentially
4 a strong benefit of the regulation protecting consumers
5 from exploitation, and this is true even in a
6 competitive context.

7 So here's the starting model, my starting
8 point. It starts out at time zero. That's a
9 contracting phase. At this point, differentiated firms
10 have a chance to offer a nonlinear contract, which I
11 will explain in a second. Consumers decide to sign up
12 or pick an outside option. Two subsequent time
13 periods, consumers make a perfect decision so this is
14 to try to make this as simple as possible.

15 These purchase decisions are binary -- buy or
16 not buy -- so I pick a quantity that's either zero or
17 one after I learn my value for the object. -So, if you
18 think of this as cell phones, I have the possibility of
19 making zero, one or two phone calls on the billing
20 cycle. At time one, I learned my value for the phone
21 call is V_1 so I decide: Do I make it or not?

22 Now I can make sense of what this contract
23 is. The contract essentially would offer some fixed fee
24 and plus a marginal charge for the total usage, plus a
25 penalty fee if you buy both units, so I think of this

1 penalty fee as applying. If you buy both units, then
2 potentially there's an additional marginal charge which
3 I'm calling a penalty fee.

4 I have some standard risk neutral payoffs
5 here. Consumer utility has an additive brand shock
6 that's going to allow me, for instance, to think about
7 a Hotelling duopoly where firms have some market power
8 and firms have constant marginal costs.

9 So if consumers were attentive, that would be
10 the end of the story. I'm going to allow consumers to
11 be inattentive, which I'm modeling as having imperfect
12 recall, so at time two, when they're making their
13 second buy or not buy decision, they can't remember
14 whether or not they purchased in the first period. And
15 hence they can't condition their choices to buy in the
16 second period on whether or not they bought in the
17 first period.

18 In this case, the optimal strategy is to buy,
19 even if your value is above some threshold V^* ,
20 where the optimal threshold is the expected marginal
21 price. So, I know I'm always going to have to pay at
22 least the base marginal fee P , but if I buy in the
23 other period, that means I trigger the penalty fee and
24 then I also have to pay the penalty fee. At time two I
25 can't remember if I bought yesterday, so I have to

1 think, "Well, what's the probability?" Well, the
2 probability is that my value was above the threshold
3 last period.

4 Again in the first period there's no memory
5 problem, but I don't know what's going to happen in the
6 future. What's the probability I'll buy in the second
7 period again? My value is above threshold.

8 The primary policy intervention I'm going to
9 consider is what I'm calling price posting regulation.
10 It's a disclosure requirement. It's the requirement
11 that the firm tell you whether this penalty fee
12 applies. Essentially because there's only two periods,
13 this is equivalent to disclosing your entire past
14 purchase history so totally solving your memory problem
15 that you can't remember how much you've used the
16 service or how much money is in your account.

17 Another intervention I'm not going to focus
18 on in the talk is banning penalty fees, essentially
19 requiring firms to charge a constant marginal price and
20 offer a menu of two part tariffs. That's going to have
21 the same quality effects as the price posting
22 regulation.

23 So the first main result in this benchmark
24 model is the equivalence result I mentioned in the
25 beginning, and this says if consumers are all the same,

1 they draw these values, VTs, from some distribution,
2 that that's the same for all customers, and they
3 correctly understand their value for their product.
4 They correctly understand this distribution F. Then
5 inattention and price posting regulation have no
6 substantive effect.

7 So welfare, profits, consumer surplus, and
8 market shares, are all unaffected, and allocations are
9 first best, whether or not there is disclosure, whether
10 or not consumers are inattentive.

11 In the attentive case, the only prices we
12 would see in equilibrium are marginal cost pricing, so
13 firms will set marginal price equal to marginal cost to
14 get the efficient surplus and extract as much as they
15 can of that as profits through fixed fees. If people
16 are inattentive, we might see different prices.

17 The only prediction of the model is that
18 prices will be set so that the expected marginal price,
19 the structure that people make to purchase decisions,
20 is equal to marginal costs. So, we're still getting
21 first best allocations in surplus, but that could now
22 be implemented with a variety of different prices,
23 including a zero base marginal charge, and the only
24 marginal charge being a penalty fee that's sufficiently
25 high that an expectation of marginal price is equal to

1 marginal cost.

2 I think this is the result that Jamie Dimon
3 should have had in his back pocket when he made the
4 following argument. He said: "If you're a restaurant
5 and you can't charge for the soda, you're going to
6 charge more for the burger. Over time, it will all be
7 repriced into the business."

8 So that's what this proposition is saying is
9 that if we have something like the bill shock
10 regulation, what it might mean is that we get rid of
11 steep penalty fees, but it's going to be made up by
12 raising marginal prices elsewhere, and the things that
13 we care about like profits and surplus are not going to
14 be affected.

15 Now, I don't actually think it's the case
16 that this doesn't matter. I think the equivalence
17 result depends importantly on all of the things that
18 are missing in that benchmark model. The first thing I
19 want to add is this heterogeneity, an incentive for
20 firms to price discriminate between different groups.
21 So, how does the model change?

22 Well, now at the contracting phase, firms are
23 not going to offer just one contract, they're going to
24 offer two contracts, a low contract and a high
25 contract. Why is this? Because there are two types of

1 consumers, those that are receiving a low signal and a
2 high signal. What's the difference between these two
3 groups? Well, at times when they're deciding, "Should
4 I make the call or not" or "Should I make the
5 transaction or not," the value draws that they're
6 getting are coming from different distributions, from
7 either a high distribution or a low distribution. So
8 high consumers are ones who have higher values to the
9 product and so they're more likely to buy.

10 Here I'm going to focus on the case where I
11 have two duopolists who are located at opposite ends of
12 the Hotelling line and consumers uniformly distributed
13 along it. There again I have different transportation
14 costs for high consumers and low consumers. Think of
15 the high consumers, they're willing to pay more to
16 purchase to make phone calls. They're a high income
17 group. They're also more willing to pay to go to their
18 preferred brands. They have higher transportation
19 costs, H , and the lower consumers have lower
20 transportation costs, L .

21 The first result familiar from standard price
22 discrimination models would be if the consumers are
23 attentive, they can keep track of their usage, and they
24 know what the marginal price is at any point, firms are
25 going to offer contracts that are going to include

1 penalty fees. In all, equilibria allocations are going
2 to be inefficient.

3 The high type is going to get a contract with
4 marginal cost pricing and make the efficient allocation
5 first best. The low type is going to choose a lower
6 fixed fee contract with marginal prices above marginal
7 costs, and their allocation is going to be distorted
8 downwards, so there's necessarily going to be an
9 inefficiency there.

10 What's interesting is when consumers are
11 inattentive, we needn't have that inefficiency, and we
12 won't in a fairly competitive market. So I want to keep
13 these transportation costs positive if they are
14 actually equal to zero. If we had perfect competition,
15 then pricing would just be at cost. There would be no
16 penalty fees. There would be no scope for disclosure,
17 so I allow it to be positive so there's some market
18 power, but small so this is a fairly competitive
19 market.

20 In that case -- in a unique symmetric pure
21 strategy equilibrium -- allocations are first best.
22 There's no distortion, although firms are charging
23 different markups, and there are surprise penalty fees.
24 And firms endogenously choose not to disclose at the
25 point of sale whether or not they apply, and prices

1 could include where the best marginal fee is zero, but
2 penalty fees are high so they expected marginal prices
3 are equal to marginal costs.

4 So what this means is if we impose price
5 posting regulation, that nice efficiency that allows
6 the pricing goes away so it's counterproductive. Having
7 price posting regulation would lower welfare. It would
8 hurt firms. It would hurt some consumers but benefit
9 others, and I'm going to skip the intuition for that
10 unfortunately, but my interpretation here is that the
11 bill shock regulation should be applied with caution.
12 You really need to be worried if you think people have
13 correct beliefs, and it is a fairly competitive market.

14 I'm going to skip this. So in the third
15 model, I assume that people underestimate their demand
16 for the service. If people are unbiased, the thing
17 about a monopoly now is they're all the same so there's
18 no price discrimination. I would fit marginal pricing
19 into the marginal cost so they get total surplus.

20 The blue bar would be at first best, the
21 dashed line, firms have captured all for a fixed fee,
22 consumers would get none. If consumers underestimate
23 their demand, we can't charge them their full surplus
24 upfront for a fixed fee. They don't anticipate it, so
25 we have to charge it, capture it through high marginal

1 fees. Allocations are distorted. Total surplus goes
2 down, and firms can't capture all of it. Consumers get
3 some.

4 With inattention, in addition to this bias
5 and beliefs, it's ambiguous whether total surplus goes
6 down or up, but consumers no longer need to get at
7 least their outside option. They can be exploited in
8 the sense that their utility can be negative relative
9 to their outside option. Firms can capture more than
10 the entire surplus, so it's ambiguous whether the
11 regulation in this case would be good or bad for total
12 welfare, but it would definitely protect consumers from
13 this type of exploitation.

14 So one of the things that's important to know
15 here is if we have a good with no social value or if
16 people underestimate its value, it's not going to be
17 sold so everybody gets zero, so they're unbiased. But
18 if they're biased, the underestimated value is
19 attentive, that remains true, but if they're also
20 inattentive, you could end up having a business that
21 starts up and starts selling a product with negative
22 social value just to earn money on penalty fees.

23 So that if the social surplus is negative,
24 consumers do very badly and the firm actually makes
25 money. I think that's interesting to note because when

1 this new federal regulation came in and required banks
2 to ask consumers, "Do you really want overdraft
3 protection before they started giving them services and
4 charging the fee," Bank of America, who had been
5 earning about \$2-billion a year from these fees,
6 decided to end the service rather than asking consumers
7 if they would like it. So this is possibly one
8 explanation.

9 So to conclude, when consumers are
10 inattentive, if you think everybody is the same,
11 there's no price discrimination going on and if people
12 have correct beliefs, then this is not a non issue. If
13 there is scope for price discrimination because people
14 are heterogeneous in fairly competitive markets,
15 inattention combined with penalty fees can be socially
16 valuable, and disclosure regulation could be
17 counterproductive.

18 When people have biased beliefs, it's
19 ambiguous whether the regulation would be good or bad
20 for total welfare, but it might be that the larger
21 factor is that the regulation protects people from
22 exploitation. I think these two results fit nicely to
23 cell phone pricing and overdraft fees.

24 DR. LAIBSON: Thank you. We now have Ginger
25 Jin to discuss the paper from the University of

1 Maryland.

2 DR. JIN: I really appreciate the opportunity
3 to read and discuss this interesting paper. The
4 question Mike asked is very simple: What happens if
5 consumers do not pay attention? This is a very timely
6 question for many consumer protection policies, and
7 Mike tries to be very ambitious and comprehensive in
8 this paper.

9 It was like after I turned the page, I would
10 say to myself, "Oh, I bet he doesn't mention this," but
11 then he mentioned it in the next page. Not only does he
12 try to capture attentive and inattentive consumers,
13 he's also considering whether the consumers have a
14 correct or biased belief about future demand and
15 whether the future consumers are homogenous or
16 heterogeneous with competition on the supply side, a
17 monopoly to competition and different types of consumer
18 protection policies that we could imply in this market.

19 So when I read the introduction, I thought
20 there were some results that are pretty intuitive and
21 some results that are surprising. The not surprising
22 ones are that firms for sure are going to exploit
23 consumer inattention and underestimation of demand.
24 Consumers would exercise price discrimination whenever
25 it's possible.

1 What's surprising is the equivalence results
2 when consumers are homogenous and have the right
3 belief, which was very surprising to me when I first
4 read it. Of course after the model, I find it
5 intuitive that firms can replace the penalty fee with
6 other charges and don't change anything.

7 A more surprising result is in the fairly
8 competitive market with heterogeneous but unbiased
9 consumers actually allowing penalty fees would be good
10 for the whole society. My take is that that's because
11 with the penalty fees, it gives more room for the firm
12 to price discriminate in a less distorting way, but
13 when we restrict the potential pools the firms can use
14 for price discrimination, then it could generate more
15 distortion in the process of price discrimination.

16 The last message I'm taking from the paper is
17 that the transparency regulation could be more
18 important in terms of redistribution of surplus between
19 the firms and the consumers, rather than enhancing the
20 total welfare.

21 So, I have some comments. The first is
22 exactly how should we think about consumer inattention?
23 Mike has been very clear about what he is considering.
24 He's considering consumers who do not pay attention to
25 their past usage. However, consumers are fully aware

1 of their future inattention, so they take that when
2 they sign the contract, so they have an expectation of
3 the future penalty fees and so forth. And they also
4 have a belief on future demand on whether that belief
5 may be correct or biased.

6 I can think of situations that are probably
7 more general than this considered set of consumer
8 inattention. For example, when they sign a contract,
9 consumers may not pay attention to all the contract
10 terms, including the fine print and so forth, and even
11 if they pay attention, some contract terms could be
12 waived or hidden.

13 "We reserve the right to change the price in
14 the future." Well, what does that mean? And consumers
15 may not realize the risk they're exposing themselves to
16 when they sign a lock in contract. People would have a
17 belief on the future demand if it appears that we can
18 impose a probability of distribution on that, but if we
19 walk away from that assumption, it's possible that the
20 consumers don't know what kind of distribution they
21 should put on that future demand.

22 Another comment is on the consumer protection
23 policy. My take of the whole paper seems like the need
24 for consumer protection policy is driven by consumer
25 underestimation of the demand.

1 Well, supposing that is true, does that mean
2 that we should actually target consumer education
3 instead of firm regulation if you think of sort of the
4 reason driving for this kind of inefficiency? If
5 consumers do not pay attention, maybe we should educate
6 them? While 20 percent of people who use our service
7 actually end up paying penalty fees somewhere down the
8 road, that will be an affirmative message to me so that
9 could be alternative policies, not just banning firms
10 from imposing penalty fees and requiring firms to post
11 the price.

12 A deeper question I would like to ask is:
13 Why do consumers underestimate demand? Of course there
14 are allocations in the future I cannot foresee right
15 now, so that could be how I could underestimate it or
16 overestimate it. On average I may be right, but
17 another reason could be I'm not familiar with the
18 future service. Like when I purchaser cell phone for my
19 husband, he was 100 percent sure that he didn't need a
20 phone at all, but of course one month later, he could
21 not live without a phone.

22 So you just don't know what you're buying
23 yourself into, and then your estimation about the
24 future demand could be way off the mark. And so that's
25 kind of saying that the demand under that estimation is

1 something that's maybe not completely exogenous.

2 The third one is if I'm thinking the consumer
3 protection policy would reduce the penalty fee and
4 reduce the surprises down the road, it's encouraging
5 consumers to be attentive. Would that have long run
6 consequences, like we'll have more people talking on
7 the phone while driving and we'll have more people
8 overreacting to their bank account and -- probably
9 several years later -- file personal bankruptcy because
10 they didn't take care of their finance when they should
11 have taken care of it?

12 So those are some things that I know are not
13 in Mike's model, but when we consider the consumer
14 protection policy, maybe that's something we should
15 take into account.

16 I can think of several directions to extend
17 this already comprehensive theory. One is attentive
18 versus inattentive is an endogenous choice, but I know
19 I may not have time to pay attention to my electricity
20 bill or cell phone bill, but can I choose to opt-in to
21 the price posting regime before I sign a contract so
22 that I force myself to pay attention to it?

23 If the underestimation of demand was driven
24 by the addictive nature of the service, then the
25 penalty fee might in some ironic way limit that

1 addiction.

2 Some factors not considered in the paper
3 might be important, like risk aversion, how long I'm
4 locking myself into the contract, or what the switching
5 costs are. If I dislike the surprise penalty fee can I
6 switch out with a reasonable cost? All those help
7 interact with inattention.

8 The last one I think Mike mentioned a little
9 bit in the paper is that the penalty fee and
10 restriction definitely are related to the design of
11 different usage plans. So is it because there are so
12 much penalty fees for calling over my limit, that it
13 will force me into signing up for a very generous usage
14 plan, which ends up charging me a lot of dollars?

15 Overall it's an interesting paper. I really
16 enjoyed it. I find the results very stimulating, and I
17 would encourage everyone to read the paper themselves.

18 Thank you.

19 (Applause.)

20 DR. LAIBSON: Thanks very much. We're going
21 to move on to the next paper and reserve questions to
22 the end.

23 Now Jonathan Zinman from Dartmouth is going
24 to tell us more about inattention.

25 DR. ZINMAN: Great. So this is joint work

1 with my frequent coauthor, Victor Stango at Davis.
2 This is not the first time I've presented a Stango and
3 Zinman paper at the FTC, and I hope it's not the last.
4 It's very good to be back.

5 So what we're working on in this paper is
6 we're interested in limited attention and its dynamics,
7 so located and varying consumer attention with regard
8 to the payment of bank overdraft fees.

9 And so just to fix ideas -- or actually in
10 this case, keep ideas rather vague -- our working
11 definition for limited attention for the purposes of
12 today will just be that people only imperfectly
13 integrate information on their choice sets into their
14 decision making. I'll talk a little bit later about
15 how we might be able to tie some of our results to
16 different types of theory models, but for now let's be
17 agnostic.

18 So what we do in this paper is we use subtle
19 variation in survey content, in the questions that
20 people that happen to be taking surveys are asked as
21 potential shocks to attention with regard to payment or
22 incurring bank overdraft fees. So we have this panel of
23 transaction level data on consumers in our panel, for
24 reasons that I'll describe, of frequently offered
25 service, the topics of which I have not announced in

1 advance, and so these surveys have questions that
2 mention overdrafts.

3 Just to preview what we found, our attention
4 delves into whether attention has an effect on
5 overdraft fees, and we find a large reduction in
6 overdraft fee payment following what are often
7 relatively subtle attention shocks in the form of one
8 or two questions on a longer survey.

9 We find evidence of economically important
10 dynamics. Attention seems to accumulate so if you're
11 exposed to repeated shocks, if you take multiple
12 surveys over time that mention bank overdraft fees,
13 your baseline level of overdrafting drops, but both of
14 these effects -- both the immediate effect and the
15 stock effect -- depreciate over time.

16 These effects are variable. They're
17 heterogeneous, and they are largest for some groups
18 that are viewed as being "particularly vulnerable" by
19 some policy makers and consumer advocates. Affects are
20 largest in low self assessed sophistication folks. We
21 do not find differences by high versus low income.

22 So what we're not doing at this point is
23 trying to say anything about the welfare implications
24 of our results, so I just want to state that upfront to
25 hopefully put your mind at ease about the types of

1 claims that we're making or -- more to the point --
2 we're not making.

3 It may be the responses we find and the
4 underlying limited attention we think that are total
5 effects in our response. The responses to these
6 surveys, we think, indicate the underlying limited
7 attention that may or may not be suboptimal. If I have
8 time, I'll talk a bit more about that at the end.

9 Some quick motivation. Michael has already
10 given us some, and this audience is probably relatively
11 well schooled on the economic importance of overdraft
12 fees, but nonetheless these are a major expense for
13 U.S. consumers, so there have been some nice and
14 provocatively put together accurate statistics showing
15 that U.S. consumers in recent years have been steadily
16 charged more on overdraft fees than they have for
17 various types of fresh produce or even on large
18 appliances, and we certainly wouldn't want that to be
19 the case.

20 Overdraft and overdrafts and overdraft fees
21 mean different things to different banks and under
22 different contracts, but what you should have in mind
23 for today is an overdraft is basically a transaction
24 that if it is settled by the bank would result in a
25 negative balance in the checking account. So it's a

1 transaction that if it's settled produces borrowing
2 against future checking account balances, and the
3 typical fees in recent years for this sort of
4 transaction have been upwards of \$20 per transaction,
5 per loan, and this is regardless of the amount of loan.

6 One reason we got interested in the question
7 of whether limited attention might play a role in this
8 -- even before we were lucky enough to have Michael
9 start working on this - is, I think, that this seems
10 like a market that is very much an architectural
11 attribute and firms go out and advertise "free
12 checking" and distract attention from or do not mention
13 the fact that free checking is not free if you incur a
14 \$35 overdraft.

15 The first thing we did when we got this data
16 that we're using in this paper is we put together some
17 descriptive stats for our papers and proceedings paper.
18 And we found some evidence there suggesting that many
19 overdraft fees are easily avoidable in the sense that
20 many people pay fees at a point in time where they have
21 much cheaper and readily available sources of
22 liquidity.

23 So they're using their debit card to pay for
24 a transaction at point of sale, and they're incurring a
25 \$39 overdraft fee when they could have paid for that

1 same transaction with a credit card that we observe in
2 this data as having available liquidity. They could
3 have paid 30 cents to charge that transaction instead
4 of 39 bucks.

5 There's some evidence in our data here of
6 limited attention to balances of the type that I think
7 motivates Michael. If you ask people why they
8 overdraft, 60 percent of folks say, "Oh, I thought
9 there was enough money in my account."

10 We'll go on to the bank side. Overdraft
11 pricing and overdraft fees have been something that
12 banks actually consistently did well throughout the
13 2000s, so it's been a major profit center for them by
14 various metrics.

15 I think this is the final piece of
16 motivation: There's not a ton of evidence on the sort
17 of empirical determinants of supply and demand in terms
18 of nonlinear stake attention contracting, particularly
19 in household finance.

20 One of the things we hope to do in future
21 versions of this paper is speak more directly to Gabaix
22 type models and to Grubb type models as you will see.
23 I think our evidence model ultimately will have
24 something to say about the types of heterogeneity or
25 homogeneity in Michael's model, about the types of

1 biased or unbiased beliefs that's critical to Michael's
2 model, so that's the direction we hope to push.

3 On the limited attention to memory side,
4 there's a host of different theory models out there.
5 The amount of paper that tracks that side of the
6 literature, a different paper as well, our comparative
7 advantages here are not just providing empirical
8 evidence but having evidence on the dynamics. And the
9 very last substantive slide I'll show you today
10 hopefully will be on the mechanisms about how people go
11 about reoptimizing, how people go about implementing
12 these reductions in fee payments.

13 And the fact that these surveys we use as
14 attention shocks have effects also relates to a couple
15 of literatures on priming and on how surveys change
16 behavior. The data we have is 36 months of panel data
17 from checking account statements, and also from credit
18 card statements although we're not using the credit
19 card data selection in this paper yet.

20 This data is put together by a market
21 research firm, Foster, which is well known to
22 economists. They actually broke off this piece of the
23 business. It's now owned by Light Speed Market
24 Research so we have over 7,000 panelists with active
25 checking accounts that we used in this paper, and over

1 a hundred thousand panelists months worth of data.

2 So panelists entered the data typically after
3 having some other relationship with this market
4 research firm. The firm goes to them and says, "Hey,
5 we will pay you let's say a remarkably low amount, 20
6 or 25 bucks if you will sign over access to your online
7 account statements." People do so again presumably in
8 large part because they've interacted with the market
9 research firm before and trust them.

10 Once they sign over access, the market
11 research firm goes through there and scrapes data from
12 their account everyday, so that that's how we get the
13 account and transactional level data. Again because
14 this is a market research data firm, when people agree,
15 the market research firm has them take an online
16 registration survey.

17 We get some demographics and our
18 self-assessed measure of financial sophistication from
19 that survey, and then periodically the market research
20 firm offers surveys on a roughly quarterly basis,
21 although it's not quite that predictable. These are
22 all market research surveys about people's financial
23 relationships and vendors and satisfaction levels and
24 what they think of new products, both hypothetical and
25 actual.

1 These surveys are all online. They are not
2 lengthy in the sense that the market research firm
3 makes a big effort to keep them to about 15 minutes in
4 length, but because they are online surveys and a lot
5 of the questions are simple, they can contain as many
6 as a hundred questions or a couple hundred questions.

7 So then we observe our panelists' full survey
8 taking history, not just within the three-year period
9 over which we have transactional data, but also back a
10 couple years beforehand. Important for our empirical
11 strategy is these are not pre announced, so people
12 presumably have some idea that this is going to have
13 something to do with household finance, but people get
14 sent Email invitations to participate in these
15 quarterly surveys, and all it says is, "Click through
16 to take a survey." It doesn't say what the survey is
17 going to be about.

18 So let me say a few words about external
19 validity. Clearly this is a whacky group of folks who
20 have lower reservation prices for signing over access
21 to their sensitive financial information. It's people
22 who took the detailed household surveys that we use the
23 SCF or the SE analogs in the EU, are probably somewhat
24 similar along unobservables if you think about it.

25 I mean, these are people who have again low

1 reservation prices for revealing very sensitive
2 financial information to surveyors who they've never
3 met before. At least our guys have interacted with
4 this market research firm, so a whacky group of folks
5 on some difficult to observe or unobservable dimensions
6 focusing on observables. Because these folks are online
7 perhaps they tend to be younger, more educated, higher
8 income than the U.S. average, a bit more creditworthy
9 condition.

10 An interesting thing to note about the survey
11 is that by any of the metrics we usually use to proxy
12 for financial sophistication are samples, our sample is
13 relatively sophisticated. But I don't know of a clear
14 prediction on whether more or less sophisticated folks
15 would respond more or less to the types of subtle
16 attention shocks that we're interested in here, so just
17 something to keep in mind.

18 So there are 21 of these roughly quarterly
19 surveys. Six of the 21 have typically one or two
20 questions that mention bank overdraft fees. We think
21 of these surveys as potential shocks to the attention
22 or salience of overdraft fees. Everything we do is
23 within the panelists and conditional on selection into
24 survey taking or not survey taking generally.

25 Lots of people on this panel take surveys.

1 Lots of people take lots of surveys. Five of the six
2 surveys basically mention overdrafts, again one or two
3 questions. I'd give you examples, but I have to speed
4 up here to get to the results.

5 When we say they mention overdrafts, what we
6 have in mind is there's no mention of prices or outside
7 options. There's plausibly no information being
8 provided on what is in people's choice sets or what
9 might be in people's choice sets. And there's this
10 sixth survey, which really does beat people over the
11 head with lots of questions on overdrafts and plausibly
12 does provide some information.

13 So again I'll skirt over this in the interest
14 of time, but basically we're going to be looking within
15 panelists across months and looking at how overdraft
16 fee payment responds in the month that you take a
17 survey and also as your stock of overdraft related
18 surveys builds up over time. And this is all
19 conditional on whether and when you are taking our
20 other surveys that do not mention overdrafts.

21 So what we need for our identifying
22 assumption is that conditional on survey taking, there
23 are no differential, unobserved, secular dynamics in
24 overdraft fee payment across those who take relevant
25 surveys and any other survey. And so the dynamics that

1 would have to be present to confound us would have to
2 be high frequency given the timing of the surveys and
3 the nature of our findings. Again the survey topics are
4 not announced ahead of time.

5 So we find a big immediate reduction. This
6 is the same month effect, larger point estimates for
7 the least educated guys and significantly larger
8 reductions for the low self assessed financial literacy
9 guys. We find that overdraft fee payment falls as the
10 stock of taking these overdraft mentioning surveys
11 builds up.

12 We can go and see because there are lots of
13 different types of surveys and lots of different survey
14 content, and we don't find that overdraft fee payment
15 responds in the wake of people taking surveys that
16 mention gift cards or auto loans and so on and so
17 forth.

18 We do have some findings on related content,
19 and it is the case that overdraft fee payment does
20 change following taking surveys that mention other bank
21 fees. The flip holds as well, so fee payment generally
22 falls following surveys that mention bank overdraft
23 fees, and so we think this tells us something about the
24 cognitive process associations in salience.

25 So in beginning to unpack these cognitive

1 mechanics, it's important to keep in mind these surveys
2 can be affecting behaviors in several different ways.
3 One is what we most have in mind, which is an attention
4 shock or a reminder of the price schedule you face, but
5 another particular point is, given the often inadequate
6 upfront market disclosure selected, that there is some
7 information being provided. This is particularly
8 plausible in one survey that has a bunch of questions
9 on overdrafts and both reminders and information could
10 be at work here.

11 So what we find here is that that more
12 intensive survey does have an incremental effect. And
13 so does that mean the more intense survey is a more
14 powerful attention getting treatment, or is this an
15 incremental effect of information? We haven't figured
16 out a way to unpack that yet.

17 We talked about how effects depreciate over
18 time. We only find effects on the extensive marginal
19 fee payment which is consistent with attention being
20 limited in a discrete way, and I already talked about
21 attention by association and those roles.

22 So some new results that I would spring on
23 Karen, -- Sorry, Karen, but we got the versions of
24 these in late last night - relate to how people pull
25 off these fee reductions. We're finding that people

1 are in fact spending less out of their checking account
2 so you might imagine that people just transfer money in
3 or transfer less money in, but what seems to be going
4 on is people are actually spending less.

5 This includes people who never overdraft
6 throughout the sample, which is interesting to think
7 about. Spending falls particularly as balances get
8 low, especially for the never overdrafting guys and
9 most of all for frequently overdrafting guys, but
10 spending falls more globally for everyone. So this
11 raises, I think, some interesting questions about what
12 the marginal transaction is as well as who the marginal
13 inattentive consumer is.

14 One thing we'll be looking at going forward
15 is do people hold their spending constant by
16 reallocating efficiently to their credit card accounts?
17 We'll be able to measure that eventually. We don't find
18 any effect on balances, which again suggests this is
19 not about people moving money in or out of the account.

20 So just to sum up, our results suggest that
21 consumer attention to this kind of state contingent
22 penalty pricing is limited, discrete, dynamic,
23 malleable, heterogeneous in its malleability and
24 associative. And since I'm out of time, I'll pass on
25 the speculation of implications for disclosure policy

1 since Michael and Ginger have already done that ably.

2 Thanks.

3 (Applause.)

4 DR. LAIBSON: Thank you. Karen Pence will be
5 the discussant. Karen is with the Federal Reserve
6 Board.

7 DR. PENCE: Let me point you to the most
8 important sentence in this whole presentation -- the
9 one thing I do want you to take away -- which is the
10 disclaimer. I'm here in my personal capacity. I'm not
11 representing the Federal Reserve or its staff, and my
12 remarks do not represent those of the Federal Reserve.

13 So, this was a fun paper to read. It's a
14 fascinating paper. It's a fascinating market. It's
15 one I had not thought very hard about before. I
16 confess I still don't know how my own financial
17 institution handles overdrafts.

18 Overdraft fees are a huge source of revenue
19 for banks, so this similar to what John just showed you
20 displayed a little differently. In 2008, overdraft
21 fees were \$36-billion worth of revenue for banks, so
22 that was over half of the revenue they got from
23 checking accounts, and it is fees that are paid in a
24 very disproportionate way. This is from John's paper;
25 it may look familiar to him. This is a distribution of

1 the share of accounts that have overdrafts and for how
2 many months they have overdrafts.

3 So it's a huge amount of people, over 50
4 percent, that never pay an overdraft fee, and then
5 there's an enormous tail of some people who pay quite a
6 lot of fees. I think John had a statistic that there
7 are people that pay up to \$250 in fees in overdrafts,
8 which is enormous. So understandably, this has been
9 the focus of a lot of public policy concern.

10 To briefly reprise the findings: bank
11 customers that are reminded, and the way they're minded
12 is by participating in a survey about the overdraft
13 features of their account, are less likely to
14 subsequently incur overdraft fees, and it's a larger
15 effect in financially vulnerable groups.

16 The results are still preliminary. One thing
17 I think that's a little bit unfortunate is that it
18 would be nice if the authors had more variation in when
19 the overdraft surveys were asked. They're very
20 concentrated on this short period of August to November
21 2006, even though their transaction data spans a much
22 longer period of time. The authors do everything they
23 can about that. They have month year fixed effects.
24 They have person fixed effects. Nonetheless, I think
25 it would be a little more comforted if they were not so

1 concentrated on one point in time, given how much has
2 been going on in the economy over the past few years.

3 Nonetheless, if you can't see my last point
4 here, the finding is consistent across samples and
5 specifications, and they do quite a lot of robustness
6 tests and falsifiable tests so it's a fairly convincing
7 result. And as has been previewed, the Federal Reserve
8 has done all researchers a tremendous favor, including
9 John, in bringing about these revisions to Regulation
10 E.

11 So this is a wonderful natural experiment in
12 changes in overdrafts and opt-in defaults and
13 messaging. There are two key dates. One is July 1.
14 The second is October 15, but as of August 15, banks
15 could no longer provide standard overdraft services for
16 everyday debit card or ATM transaction, unless the
17 customer explicitly opts in.

18 Now interestingly it's not everything, so if
19 you write a check and that bounces, you overdraw your
20 account, the bank can still provide you overdraft
21 services. If I have a recurring payment set up, that
22 was not covered. It's just the scenario people talked
23 about. You go to Starbucks, and you slide your debit
24 card through, and you didn't know your coffee was going
25 to cost you an additional \$35. So those are the kind

1 of transactions envisioned. That's what everyday
2 means, which is now a federal regulatory term, I think,
3 in this context.

4 So, banks provided extensive messaging to
5 their customers about this opt-in choice, and I'll be
6 showing you a little bit about that messaging later,
7 but again there's a lot of interesting stuff here in
8 terms of communication. One nice thing about the data
9 that John and Victor have is that they have very, very
10 detailed information on the transaction, so in theory,
11 they could look separately at check transactions,
12 everyday debit card transactions, that kind of thing.

13 There's this really neat statistical
14 relationship in the data. You take a survey. You're
15 less likely to incur an overdraft. So for policy
16 makers the crucial question is going to be: What is
17 that mechanism? It's a neat result, but what should I
18 draw from it?

19 John highlighted two possibilities. I'm
20 going to talk a little bit about one of them, which is
21 information, and you can think of information in a
22 couple different spectrums. You can literally be not
23 aware that you're going to be charged a fee if you
24 overdraw your account or you can be unaware of certain
25 aspects of the policy.

1 Then they're going to test this in this one
2 survey module, which is much longer, much more
3 extensive. It has all this fee information. It has 12
4 questions on overdrafts, but the behavior of people who
5 took that survey, was not affected anymore than people
6 that took saw a single question, "Do you have
7 overdraft," so that makes it hard to think just based
8 on this limited information that it's information per
9 se that is the driving factor.

10 I'm going to show you a slide that I see as
11 consistent actually with his view that information
12 can't be the main factor. This is a slide from a
13 consumer research group called Mintel, which is fairly
14 similar to the one that John is using in his paper.
15 They also do Internet surveys, so this is a survey in
16 June of 2010 of a thousand adults over the Internet.

17 They were asked two questions: First, have
18 you overdrawn your account in the past six months? And
19 secondly, are you planning to opt-in, so have you
20 already opted in? Are you not planning to opt-in?

21 What I find interesting is I think incurring
22 one of these fees is probably the best form of
23 education you can have. There's nothing like paying
24 \$35 to make it very salient to you that overdrawing
25 your account is very expensive. No amount of reading

1 disclosure is going to convey that message that
2 vividly.

3 If you look here, this is all customers, and
4 these are the ones who overdrew their accounts. Of the
5 ones who overdrew their accounts, they're the ones that
6 are choosing to opt-in. I don't know if they know what
7 they're doing, but they're very clear that overdrawing
8 brings a penalty. There's not a basic educational
9 problem or informational problem, and they want the
10 service.

11 So this suggests to me that some of the
12 things John was talking about, about salience and about
13 reminders, giving people the information so they can
14 make a decision in advance as opposed to having it
15 sprung at them at the register, is actually the way to
16 think about it. It is the salience. It is the
17 reminder feature that may be the round in their data.

18 Just to finish, while we're on the subject of
19 salience and reminders, we often get from Mintel copies
20 of all the mailings that banks sent to their customers
21 urging them to opt-in, and the most frequent message is
22 actually of embarrassment. I'll read you three quotes.
23 "Let us continue to save you the embarrassment of
24 having your purchases declined and the hassle of not
25 being able to get cash in an emergency."

1 "The benefits of overdraft protection: It's
2 convenient. It saves embarrassment. It provides a
3 safety net. It's good to have in an emergency."

4 Finally my favorite: "Our intention has
5 always been to save the embarrassment and inconvenience
6 of a declined transaction."

7 So my point here is that salience reminders
8 are something in this paper promoted as a good thing so
9 they can help consumers make the right decision. I
10 think it's important to remember there are tools that
11 can be used to influence decisions in a whole lot of
12 ways, and this is a pretty stark reminder of that.

13 Thanks.

14 (Applause.)

15 DR. LAIBSON: Thanks. The third paper now,
16 Nicola Lacetera will present about limited attention in
17 the new car market.

18 DR. LACETERA: Thank you very much. It's so
19 good to be the third presenter on consumers because I
20 don't have to spend too much time saying consumers are
21 inattentive and that that seems to matter in important
22 markets.

23 What we do in this paper with my coauthors,
24 Devin Pope and Justin Sydnor, is looking at a
25 particular market, the used car market, which as you

1 know is a very large market with large stakes. It's
2 reasonably competitive, and yet the particular type of
3 inattention we will look at is not washed away by the
4 used car activities of this market.

5 But the type of inattention we look at is
6 inattention to the exact mileage of a car. Mileage or
7 odometer reading is, on the one hand, a very important
8 determinant of the price of a car, and on the other
9 hand, it is somewhat different from a good part of the
10 literature on the effect of the inattention.

11 There isn't this obfuscated or shrouded
12 component to it, so it's a fully visible thing, so we
13 can look at the odometer in the particular setting
14 which is a wholesale used car option. It's going to be
15 very clearly displayed on a monitor, so anybody can see
16 the exact mileage of the car, and yet it seems to be
17 the case that there is not full attention to the
18 mileage. And in particular we will look for this left
19 digit bias whereby we pay full attention to the left
20 most digit of the number and less so to the other
21 digits.

22 Just to organize our empirical analysis, we
23 use a framework which has been developed by Stefano
24 Dellavigna based on others' works. The idea is we have
25 two sets of characteristics affecting the value, the

1 perceived value of that good. One is a fully visible
2 characteristic, V , and the other is an opaque
3 component, so we cannot see it immediately, and we
4 don't pay full attention to it, so the attention that
5 we pay is determined by the factor one minus θ .

6 So θ in this is our measure of
7 inattention. How do we translate that in our survey?
8 We look for this left digit bias. Essentially think of
9 a number like 49,900. Think of a mileage of that type.
10 The way we think about how consumers look at this
11 number is essentially by discounting the right most
12 digit in a constant way, one minus θ , even in a
13 progressive way.

14 So the more we move to the right, the less
15 attention we pay, and there is some psychology research
16 in this, in the form of recall surveys that confirm
17 that this seems to be the case.

18 How does this translate into a valuation
19 schedule? So, let's think about the car market as an
20 example. You think of the perceived value of the car
21 being determined negatively by the mileage, and if we
22 believe in that inattention where we assume in terms of
23 valuation this discontinuity in the simplest case at
24 each and every 10,000 mile mark, it is proportional to
25 the level of inattention, of course, and to the

1 depreciation rates of the car.

2 Essentially we perceive the mileage to be
3 lower than the actual one. The valuation is always
4 higher than the actual one, which is represented here
5 by the dotted line, and it coincides with the actual
6 one, at the exact 10,000 mile mark.

7 How does that translate into auto sales? So
8 we will look at wholesale car auctions where sellers --
9 they can be dealers, they can be car rental companies,
10 and so on -- bring their cars to the auction. On the
11 demand side, we have used car dealers who will bid for
12 these cars in an ascending first price auction scheme,
13 and then they bring their cars to their lots and sell
14 them to the final consumer.

15 So in the simplest kind of model, there is
16 this representative agent in the competitive market,
17 and then we will have the price at the auction coincide
18 with the prices on the lot because of the zero profit
19 condition. And the price will reflect the perceived
20 valuation as we show sort of in this graph. We can
21 enrich the model by considering the heterogeneity of
22 consumers by valuation or by the level of inattention,
23 but the results in terms of the gaps we will have
24 stayed the same.

25 Empirically, we looked at the major wholesale

1 used car auction companies in the U.S., which gave us
2 access to their data. I was almost sure we had the
3 largest data set in the room, and I think they beat me
4 like five to one so that's unfortunate, but 27 million
5 observations seems to be a pretty large data set, so we
6 were excited about it.

7 Just very briefly, what we got was the
8 information about the car sale, the price at which it
9 sells, the exact mileage, which again is displayed when
10 a car is auctioned, and those are also available in
11 printouts, and we know, importantly, a lot of
12 characteristics of the car: the make, the model, the
13 body style, the production year. We know the year of
14 the auction, so when the car was transacted and also
15 the location of the auction. We also know the precise
16 ID, essentially the identity in a sense of the buyers
17 and the sellers, so we will use all of this information
18 in our analysis.

19 So let me start by giving you a sense of what
20 the whole data looks like. So what happens if we plot
21 on an X axis mileage and on the Y axis average price?
22 We see that something is going on, right?

23 We see that there is a decline, of course,
24 and we see discontinuities pretty much in each and at
25 every 10,000 mile mark. If we go and look very

1 closely, we see that also each point represented a 500
2 mile bin. In a sense there seems to be a little bit of
3 inattention also in the sort of four digits, if you
4 want, the small ones.

5 So there seems to be something, and of course
6 we can from the raw data interpret this exact mileage
7 so we can actually give some numbers. For example, as
8 we cross 80,000 miles, we have a difference of about
9 \$200 while as we stay very close to 80,000 miles, but a
10 little bit under 70,000, it's just \$10 for each hundred
11 miles of the older cars.

12 So can we assign this to inattention? Is it
13 the right size? Maybe there is some selection going
14 on? So, for example, the seller might anticipate that
15 this will happen, so they bring different types of cars
16 on one side or the other of the 10,000 mile mark.

17 To the extent that this car differs on
18 features that affect the price, we can actually have
19 some buyers estimate. And something like that might
20 actually be going on if you look at the volume
21 patterns. So this is the number of cars brought to the
22 auction by mileage, and you see some weird things going
23 on.

24 I'll explain in a moment what is going on
25 around the 30,000 mile, but in general, we see some

1 peaks right before each 10,000 mile mark suggesting, in
2 a sense, that maybe there is some timing, so to speak,
3 in which cars are brought to the auction.

4 So one way to sort out this selection effect
5 is essentially to look at receipts, so we had a lot of
6 information about the cars. We can construct this very
7 detailed fixed effect for each car, make, model, model
8 year, body style, up to the auction location, auction
9 year and even the ID of a given seller. We can look at
10 the regression of the price on these fixed effects, and
11 this discontinuity stays there.

12 By the way, doing this kind of analysis is
13 the same as running a regression discontinuity kind of
14 analysis in which essentially those discontinuities are
15 equivalent to the estimate of these dummies on these
16 10,000 mile mark changes. Again we see that also for
17 the thousand miles; we see this kind of pair. It's
18 very difficult to see -- it's small of course -- but
19 it's there.

20 We also decided to go after the issue of
21 selection by looking at the two different classes of
22 sellers we have in this data. So, on the one hand
23 sellers are new car dealers who are trading in and they
24 decide to bring it to the auction. On the other hand,
25 we have Hertz, Enterprise or financial companies

1 getting rid of their leased cars, so for the dealer
2 sellers, we might be concerned about selection and what
3 kind of cars they bring to the auction as opposed to
4 those that they keep on their lot.

5 They may have a higher reservation price,
6 and, for example, they might be much less likely to
7 sell a car. It's actually about 70 percent of the
8 cars sell as opposed to the other type of sellers,
9 fleet and lease as the company has classified them.
10 They actually sell almost all of their cars just to get
11 rid of them.

12 So selection issues seem to be less of a
13 problem there, and in fact we see the spikes in say
14 bringing a car to an auction for the fleet/leases cars
15 around 36,000 and 48,000 miles. That depends on the
16 structure of the lease, four-year 48,000, or a
17 three-year 36,000 miles, but these peaks are typical of
18 the fleet/lease cars, those peaks in volume right
19 before the 10,000 mark, so there might be some
20 selection effect where it's important to control for
21 the fixed effect.

22 Once we do that and we see that the patterns
23 are very similar across the two types of sellers, so
24 these are the same procedural graphs, but separating
25 the two types of sellers. It also is important if there

1 may be other alternative explanations that we need to
2 take care of.

3 So first of all, one could say, "Okay, you
4 convinced me that all the unobservable characteristics
5 we need to account for this selection; how about
6 unobservables?" We believe that in this setting,
7 prices are determined by the characteristics that we
8 can actually see in our data, so it might not be too
9 much of an issue.

10 We still need to be concerned about those
11 peaks right before the marks, but the whole schedule of
12 price actually shifts down, not just around the marks
13 so that those will make us less concerned.

14 Of course a major issue is warranties. Maybe
15 people just discount the warranty structures as an
16 instructional characteristic. Fair enough, but we
17 don't observe what it is for all of the 10,000 mile
18 mark. We also analyze separately makes from which we
19 have more detailed information on the warranty
20 schedule, and we can rule out essentially that
21 explanation as well.

22 Maybe people cheat, and they tamper with the
23 odometers or they bring it back a little bit. We don't
24 have empirical evidence of that, of course. This is
25 something they don't tell us about, but this will bias

1 our estimates downward. These people anticipate
2 there's some probability that this might be going on.

3 What about the differences across time? We
4 do see some heterogeneities across cars, right, so for
5 some cars, the discontinuity is higher than in others.
6 Actually the simple model presented gives an
7 explanation for the idea that the higher the
8 depreciation, the higher the discontinuity should be.
9 And that's what we find in the data.

10 So then we wondered: Well, maybe people just
11 look at the books like Kelly Blue Book and Edmunds, and
12 those books are discontinuities, so they just follow
13 what they see there. Again for Edmunds, they actually
14 use a new procedure where there is no discontinuity.
15 With Kelly Blue Book, you will see if you plot data
16 there are some discontinuities, but it's not
17 systematic, not at the 10,000 miles mark.

18 So again even the sort of institutional
19 explanations don't explain this. Since now I'm
20 employed by a Canadian institution and my discussant is
21 Canadian, I thought that I should say something about
22 the Canadian data which we rely on just for a few
23 auctions. As it turns out for the Canadian auction,
24 the discontinuities are at the 10,000 kilometers mark,
25 and we run it as a perceived 10,000 mile mark as well.

1 We don't see any discontinuity in the 10,000 mile mark,
2 and this is consistent with this left digit bias.

3 Now, it's kind of interesting to understand:
4 Who is inattentive? We have different buyers at the
5 auction, and the results we find in particular are
6 consistent observationally with two cases. One is in
7 which the buyers at the auction are fully savvy and
8 they just anticipate the final consumers not being
9 attentive, and another is where the buyers at the
10 auction and the final consumers share the same bias,
11 and that's where we cannot tell them apart.

12 We do not have conclusive evidence because
13 of these observation equivalents, but what we can do is
14 to look at more experienced buyers. Those that come
15 more often to the auction are more likely to buy before
16 the threshold, so they do not perceive it as
17 overpriced, and they can anticipate they can sell the
18 car for more.

19 We also observe, if we look at the data, that
20 the drop begins actually before the 10,000 mile mark,
21 and you have to drive your car back to the lot, and
22 there are going to be some test drives. You want to be
23 sure by the time the car is sold that it is still below
24 a 10,000 mile mark. And we actually called and talked
25 to some of these dealers directly and they said, "Yeah,

1 actually we make sure that when we test drive cars,
2 they don't go over the 10,000 mile mark."

3 So we conclude that most of these buyers
4 should be on the side of the final consumers who are
5 then the ones that bear the mispricing implied in
6 these.

7 Finally we would like to give an estimate to
8 the amount of the inattention or the degree of
9 attention, the theta parameter in that model. We go
10 after that in different ways, so as you can see, there
11 are very simple linear ways in which mileage entered
12 the equation.

13 We can estimate the theta by looking at the
14 gaps and estimating the depreciation and back out the
15 theta, which is around 30 percent. Similar results use
16 a nonlinear specification with a flexible polynomial in
17 miles rather than the heterogeneity in the price
18 discontinuity.

19 If you essentially regress the gaps you
20 observe on the side of the discontinuity, the
21 coefficient that we estimate should be our theta, and
22 again we find it to be in around .3, which implies that
23 30 percent of the price decrease can be explained by
24 this gap at the 10,000 mile mark.

25 So to conclude, we find evidence of these

1 buyers being present in the market, being in the order
2 of discontinuities between 150 and 200 dollars. This is
3 mispricing if you integrate 2 to 3 billion dollars and
4 if you believe that it is the final consumers and these
5 buyers, they're the ones from which the welfare is
6 effected. We also see an effect on supply decisions
7 because we see these patterns, so it seems that these
8 buyers affect different aspects of these markets.

9 One could ask: Is it a rational thing to do,
10 not to pay attention? There is some cost and people
11 factor in these costs. In this case, in this setting,
12 it's easy to look at the odometer. You buy a car with
13 9,999 miles, and you know that in a matter of few days,
14 you will cross the 10,000 mark. It's also true that we
15 wouldn't expect the discontinuity to be bigger for cars
16 with higher depreciation because the cost of the
17 possessing that information shouldn't depend on both,
18 but I think the evidence is more toward an irrational
19 type of inattention rather than a rationale one, but we
20 don't have fully definitive answers.

21 Of course we speculated that there are many
22 other settings where it happens. The numeric measure
23 is important in decision making. Think of GPA for
24 hiring or SATs for admission decisions. Think of
25 accounting measures for financial evaluations and so on

1 or medical measures, pressures, weight of babies,
2 newborns and so on.

3 That's where understanding better this type
4 of left digit buyer and the effect on market and
5 decisions would be totally relevant in future research.

6 Thank you very much.

7 (Applause.)

8 DR. LAIBSON: Kory Kroft will be our
9 discussant from Yale.

10 DR. KROFT: Thanks for the opportunity to
11 discuss this paper. There are a few things I would
12 like to say at the outset before getting into some
13 detailed problems.

14 The first is that there's growing literature
15 on the importance of inattention, and the majority of
16 studies in this area come typically from lab
17 experience, lab experiments, and this paper is
18 different in the sense that it focuses on a naturally
19 incurring market and uses observational data.

20 So, one of the contributions is estimating
21 the importance of inattention in an equilibrium
22 setting, focusing on the steady state, which I think is
23 interesting.

24 The second departure from the previous
25 literature is that typically other papers have focused

1 on situations where information is shrouded and
2 typically there's been some experimental manipulation,
3 and in this context, information is not shrouded, in
4 the language of Zinman and Laibson. So, it's more
5 impressive if they find that inattention is important
6 because information is available at no cost.

7 Apart from the fact that the evidence is
8 extremely credible, the last thing I wanted to say at
9 the outset, or at least one thing I liked about the
10 paper, is they had a really nice simple framework and
11 intuitive behavioral model for interpreting their
12 evidence, which delivered a parameter with a nice
13 interpretation, and others have estimated it so that
14 they can see how inattention in their context relates
15 to inattention in other contexts.

16 A few things I would like to discuss and I
17 won't grapple too much with the empirical evidence, but
18 I wanted to talk about how we interpret some of the
19 estimates, and I wanted to say something about welfare.
20 Nicola talked little about this volume response, so I
21 won't talk about that, and finally we'll conclude with
22 the empirical test of final consumers versus used car
23 dealers.

24 So the claim of the paper is that θ , that
25 they interpret this by saying 30 percent of the

1 depreciation that a car experiences due to mileage
2 increases occurs discontinuously at 10,000 mile
3 thresholds, and I don't want to push too hard on this,
4 but there are sort of several caveats that I wanted to
5 mention.

6 The first, and I could be off on this, but
7 the way that they're getting this estimate is basically
8 to compare the discontinuity to the rate of
9 depreciation, and I wonder whether one wants to
10 estimate the rate of depreciation using raw prices or
11 residuals. And I think the way they're getting the
12 depreciation rate is basically they're holding the age
13 of the car fixed, so I wonder if you want to use an
14 unadjusted or adjusted price. So, I wasn't sure about
15 that.

16 Then the other comments with respect to the
17 interpretation of θ is it sounds like 30 percent
18 relies to a large extent on the model, so the way I
19 think about this decision is going out and buying a car
20 and having a decision where you think you're going to
21 drive that car for a couple years or 30 or 40,000
22 miles, and then at some point you think that you're
23 going to sell the car.

24 And it's at that time where the margin of
25 whether to sell it at 49 versus 50,000 comes into play,

1 and if you think about that sort of a model, then
2 inattention and that kind of a decision problem seems
3 more like sort of a local phenomena in explaining
4 depreciation.

5 In the estimates for accounting depreciation,
6 I think you might want to consider outside the model to
7 what extent it accounts for the depreciation of the car
8 and also the potential welfare cost.

9 So Nicola mentioned that not only do we
10 observe a difference in price for cars below mileage
11 thresholds and cars at the mileage threshold, but also
12 observed sellers responding to the threshold in the
13 sense that sellers were more likely to bring their cars
14 to the auction right below the threshold.

15 And if you think of that as a supply
16 response, one question is whether that effects the
17 equilibrium price per car, so if sellers are responding
18 endogenously to a higher price increase, then one would
19 think that that has some effect on the price of the
20 car. And I know they came at from the standpoint of
21 focusing on whether there's a selection effect which I
22 think is important, and I'm, kind of convinced that
23 there isn't a selection effect going on.

24 I wonder whether the price difference might
25 even be greater once you account for the downward

1 pressure due to the supply response.

2 Finally, it might be interesting just to
3 study the volume discontinuity of dealers as an outcome
4 rather than something to look at in terms of a
5 selection problem. You might think that's a function
6 of the parameters of the model, so it might be
7 interesting to think about how to model the volume
8 discounts or in addition to the price discounts really.

9 So in the interest of time, I'm going to skip
10 over some of this. I'll just talk about some related
11 research ideas that you might be able to explore in the
12 data.

13 One of the nice advantages of this data set
14 is they have data from the U.S. and Canada, so one
15 thing that Canadians talk about is if you take two cars
16 that are identical in terms of the model and make and
17 mileage, and one car is expressed in miles and the
18 other one is expressed in kilometers, do you observe a
19 different price just given that the one car is
20 presented in kilometers?

21 So I don't know if you have enough power in
22 your data to test this, but it could be interesting to
23 see conditional on what make and model and mileage,
24 whether just changing the metric that the mileage is
25 presented in has an independent effect on price. And I

1 think it fits in with your attention framework.

2 And then another phenomena that people talk
3 about in car auctions is that price seems to be based
4 on the age of the car in terms of calendar years rather
5 than months. You could imagine comparing two cars, one
6 purchased right at the end of the year and the other
7 purchased right at the beginning of the year -- two
8 cars that are kind of observationally the same -- and
9 see if you find any difference in price.

10 Again you have 20 million transactions, so
11 you could potentially be able to do this, but I don't
12 know if you have sufficient power there. Overall I
13 thought the paper was well executed with really nice
14 empirical evidence and very impressive.

15 So well done.

16 (Applause.)

17 DR. LAIBSON: Given that we started late,
18 we're right on time, but we don't have a lot of time
19 for questions.

20 Do the authors have urgent responses that
21 they want to make to the group?

22 Let's just jump right to a handful of quick
23 questions, and I'll accumulate the questions, and then
24 we'll just answer them in one fell sweep.

25 DR. FARRELL: I have a fundamental

1 observation which I think is prompted by Michael
2 Grubb's paper, although I haven't read it yet. I plan
3 to.

4 And that is that very generally, if you have
5 market power or any situation where there's going to be
6 a price above marginal cost, there is a total welfare
7 gain in the model by bamboozling consumers into not
8 paying attention to that price above marginal cost. And
9 yet as an enforcement matter, I think it's crucial not
10 to put too much weight on those welfare gains.

11 One question is: Is that's what's going on
12 in your paper? And then a question for the group as a
13 whole is: What's the right way for economists to say,
14 "Yes, that's there, it's in models, but if you agree
15 with me, we don't want to put very much weight on that
16 from an enforcement or policy point of view?"

17 DR. LAIBSON: We're accumulating questions.

18 DR. INDERST: This is a very general comment
19 to the issue of the overdraft payments. The
20 presentations basically start with the idea that we
21 basically know what's going on out there, that people
22 are basically fooled, et cetera, and possibly something
23 should be done. And there was a moment where I think
24 one of these authors, he said if we save payments, how
25 much it would bring us in terms of groceries we can

1 buy.

2 But two very short comments on this, and they
3 all kind of come back to the issue of pricing bundles.
4 First, cross country evidence, if you look at different
5 countries, even different European countries, you see a
6 variety pricing plans for banks to make money with the
7 retail customers.

8 So in some countries you pay a fixed amount
9 for an account and in some countries nothing. Does that
10 mean we have different regulations? Does this mean we
11 have consumers with different neural stuff going on?
12 So, how do you explain that?

13 Possibly there is a wide variety basically of
14 how customers are charged, and it's not clear to me
15 what could explain this.

16 Maybe inattentive consumers could be one
17 reason, but to me it's not quite obvious why in some
18 countries it could be more and in some countries less.

19 Related to this, a very short comment: If we
20 don't think about the multiplicity out there, it's not
21 just because we get a lot of solutions to documentation
22 problems, but because there is an economic reason
23 behind one of the other pricing models.

24 Why not start with this pricing? But for me,
25 this pricing scheme where you charge less overdraft, is

1 like an efficient enterprising scheme. You're pricing
2 the most inelastic demand, so you price a bundle and
3 you put the highest price on where the demand is
4 elastic.

5 Of course the models didn't have to show much
6 because there is the demand shown.

7 DR. LAIBSON: Anyone else? Great. No other
8 hands. Let's go through the authors in the same order,
9 beginning with Michael.

10 DR. GRUBB: To address Joe -- with the short
11 time it didn't come out as well as it should in my
12 talk. The reason for why penalty fees can be socially
13 beneficial in the model of price discrimination is that
14 they allow price discrimination with smaller
15 distortion.

16 I'm not quite sure if it matches what you
17 raise, but the idea is: If I can charge a low-based
18 marginal charge and a high penalty fee in such a way
19 that the expected marginal price is actually equal to
20 marginal cost, it's actually efficient.

21 I've got more degrees of freedom. When
22 people are attentive to get people to choose the
23 efficient amount, the marginal price for ever unit has
24 to be equal to marginal cost. When people are
25 inattentive, I can have different prices for different

1 units at different prices, so the expected marginal
2 price is still marginal cost, so you still make
3 efficient decisions.

4 But the extra freedom helps me sort people
5 into different contracts, essentially because a high
6 demand consumer, when you think of the expected
7 marginal price, is higher because they're more likely
8 to pay that penalty fee, but they're not choosing that
9 contract, so that doesn't create an inefficiency. I'm
10 not sure if that helps get at your question.

11 To Roman's point about the cross country
12 variation, I think I don't have a good answer. That's
13 something I would like to actually learn more about,
14 the variation, and something I would love to try and
15 understand better.

16 DR. ZINMAN: So in response to Roman's
17 comment, one reason we punt on trying to say anything
18 about welfare implications of the results of our
19 consumer responses is we're aware that there's a supply
20 response. And, indeed, the time path of bank pricing
21 strategies in this market has been fascinating and is
22 very much worthy of continued explanation.

23 The one thing I would say in terms of your
24 notion of this: I was thinking about this in a Ramsey
25 model and I think you would need some additional

1 gyrations or richness to capture the fact that when
2 people are exposed to something like a relatively
3 subtle attention shock, that their demand changes. But
4 other than that, I take the big picture point you're
5 making as absolutely on point and something that merits
6 further work.

7 MR. LAIBSON: Nicola, do you have anything to
8 add?

9 DR. LACETERA: No, I think the comments were
10 great and thank you.

11 DR. LAIBSON: Let's thank the authors again.
12 When are we going to reconvene?

13 DR. ROTHSTEIN: 3:40.

14 (Whereupon, a brief recess was taken.)

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25 PAPER SESSION THREE: CONSUMER CHOICE IN NEW MARKETS

1 FIONA SCOTT MORTON, CHAIRPERSON, YALE UNIVERSITY SCHOOL
2 OF MANAGEMENT

3 PRESENTER: DIRK BERGEMANN, Yale University

4 DISCUSSANT: DAVID BALAN, FTC

5 PRESENTER: STEVEN PULLER, Texas A&M University

6 DISCUSSANT: TIM BRENNAN, University of Maryland,
7 Baltimore County and Resources for the Future

8 PRESENTER: EUGENIO MIRAVETE, University of Texas at
9 Austin

10 DISCUSSANT: JACK HOADLEY, The Health Policy
11 Institute, Georgetown University

12 DR. SCOTT MORTON: We now have the session on
13 Consumer Choice in New Markets, and we're starting with
14 Dirk Bergmann from Yale University.

15 DR. BERGEMANN: Thank you and I'm very happy
16 to be presenting. This is joint work with Alessandro
17 Bonatti, and this work really begins with the
18 observation that advertising on the Internet brings an
19 important way for sharp views of advertising in more
20 traditional media.

21 Traditional media is basically every viewer
22 was listening to a particular program, maybe think
23 about radio. Every television watcher was watching a
24 particular program, and was faced with the same
25 advertising, and conversely, advertisers have very

1 limited ability to reach a particular audience with
2 particular characteristics they might be interested in.

3 With the Internet, that's quite different.
4 Just think of a search. When I put in a search for,
5 say, mountain bikes, and clearly I'm revealing a lot of
6 information that I'm interested in, what I might be
7 interested in consuming, and many advertising firms
8 basically share, to a large extent, some parts of the
9 search, so think about this for advertising.

10 If I'm looking or if I'm reading a blog on
11 bicycling, clearly there might be some inference to be
12 made about my interest in bikes. And if my browser
13 tracks my browser history, then again I can basically
14 infer when I'm reaching the next advertisement or the
15 next website, what my possible interests are.

16 So there's a sharp break in new abilities in
17 terms of providing a match between a consumer, his
18 preferences and then the advertiser. So, one view of
19 the Internet is that basically society is going on the
20 Internet and as it improves over time, as it increases
21 the quality of the match between the consumer and the
22 advertiser, we basically get a much better and better
23 match between the interests of the consumers and the
24 advertisers.

25 Of course although it has an impact which has

1 been well documented in all the competing advertising
2 media in the sense that there would be a shift away
3 from the traditional media, which has less ability to
4 target, to the Internet or other electronic media,
5 which has a higher ability target.

6 I'm just giving you sort of a time series
7 here, and what you see is that over the last few years,
8 there has been a change, a dramatic change in terms of
9 the composition of how advertisers place the
10 advertisements across a different media, and therefore
11 what we would like to do in this paper is try to first
12 understand what the implications of targeting are in
13 terms of how the advertisers allocate advertising
14 across different media, in particular with regard to
15 the implications for large advertisers versus small
16 advertisers, and then second we want to understand what
17 the role of targeting technologies is in the
18 competition across different media.

19 So that's basically the outline, and in order
20 to do that, we basically want to think about
21 advertising as a matching process, as a matching
22 process under substantial friction. Some of the
23 friction comes clearly from the fact that as an
24 advertiser, I may typically send out messages or I may
25 place advertising where I may not reach the audience

1 I'm interested in. These are lost information, and then
2 also there's a cost of duplicating. I might have the
3 right audience, but trying to send the same message
4 over and over again, that's something which I also want
5 to avoid.

6 The idea of targets is basically that they
7 allow me to reduce a friction, and therefore they lower
8 the cost of the advertising. So the way I want to
9 think about this, and to really think about the
10 heterogeneity markets both in terms of customers being
11 heterogeneous and also firms being heterogeneous, is
12 that we want to think in a two dimensional world.

13 On one side are the advertising markets, I'm
14 going to label them as A, and think about these as
15 basically different media, different websites,
16 different communication channels. On the other side, we
17 have heterogeneous consumers and each one of them is
18 basically just interested in a particular product, so
19 they're single minded in the sense that they just want
20 to buy a bicycle or they just want to buy roller blades
21 or something like that,

22 We want now to think about the consumers
23 basically being distributed across media markets, and
24 also across product markets in a sense that that is
25 dangerous, so a consumer is basically characterized by

1 two dimensional times. One, what's the media where we
2 can find him, where we can locate him, where we can
3 reach him, and the other is: What is his interest,
4 what is his preference, what can we convince him to
5 buy?

6 You want to think about market structures in
7 this world, and basically you want to think about the
8 distribution. Although the consumers are on the one
9 side, the media market, and on the other side is the
10 preference, mainly what you would like to bring? This
11 two dimensional representation of course then suggests
12 that we may want to look at the cross-section.

13 That is, we want to say in a particular
14 advertising market, and that is sort of the vertical
15 lines, we are interested in what are consumers who are
16 reading this media or following this newspaper
17 interested in? What are their preferences? And
18 likewise, as a seller of product X, that is as the firm
19 that sells product X, I would like to know, and that's
20 the horizontal line, where can I actually find my
21 consumers, on which media markets do I need to be
22 present and extend messages?

23 The basic exercise that we are going to
24 pursue here is maintaining as given the consumer's
25 preferences, which is this distribution of the products

1 that they're interested in, which is $S(X)$. Then we want
2 to think about what happens if the slotting, that is
3 the targeting of the consumers, is improved through the
4 targeting technology? What impact will that have on
5 the way you're going to place advertising, on the way
6 we're going to price advertising, and on the social
7 value of advertising in terms of matching consumers
8 with firms?

9 So the two extremes are clearly in this
10 scheme, the possibility of perfect targeting, a
11 consumer with interest X is only found on one
12 particular advertising market. That's the best
13 situation from the point of view of the advertiser
14 because he knows exactly where he can find his
15 customers, and on the other hand, there is sort of the
16 situation with zero targeting, when all the consumers,
17 irrespective of their preferences, are in the same
18 market or basically all the advertising markets show
19 the same composition of consumers.

20 The question we're then going to pursue is:
21 What is happening if you basically are moving from a
22 world where we have very little targeting opportunities
23 to one where we actually have a lot of targeting
24 opportunities? That's of course just a semantic
25 representation, but what you already see is that if

1 you're going to have more targeting opportunities, then
2 we will see that customers will move away from a few
3 large media to basically smaller media or websites or
4 blogs or whatever you want to think about. And at the
5 same time, in each particular market, you will find a
6 higher concentration of consumers with a particular
7 interest.

8 So, in order to make this final, we are going
9 to work in a frame work with dramatic distributions,
10 that is the preferences of the consumers follow the
11 dramatic distribution, so you think of the lambda as
12 basically the point of concentration. Products X, which
13 are nearby zero, are products which have a large
14 audience, basically are mass market products which have
15 a large X or small K. Products that have a large X are
16 basically the long tail of the market which has a very
17 small audience.

18 We also are going to assume a geometric
19 distribution of the consumers across the advertising
20 markets. So here on this scheme, what you're going to
21 see in advertising Market 1, is we will find consumers
22 which are interested in Product 1, but you might also
23 find consumers which are interested in 2 and 3 and so
24 on.

25 If you want to think in the language of

1 bicycles, think about sort of leisure bikes and then
2 race bikes. Readers who are reading Sports Illustrated
3 might be interested in leisure bikes or race bikes, but
4 if we just say regular use, which is more focused
5 towards sport bicycles, we'll only find guys who are
6 interested in more specialized bicycles. So that's the
7 sense in which these media markets are fine tuned in
8 terms of reaching a smaller and smaller audience.

9 So, that's the model that we're going to work
10 with. What we're going to think about is what happens
11 when the targeting technology becomes better, that is,
12 when the distribution to the consumers over this
13 advertising market basically reaches or gets closer to
14 a situation where we have perfect targeting, where
15 there's a perfect match of the interests of the
16 customers with the particular medium. So what I showed
17 you is that when you think about targeting, then that
18 has both a size and a competition effect on the market.

19 I mentioned that we want to think about
20 advertising basically as matching, so think about this
21 as random matching. If I'm going to send out messages
22 as an advertiser to my population on a particular
23 advertising market, I'm going to have a uniform
24 probability of reaching a particular customer. And so
25 if I'm sending out more messages, I have a higher

1 probability of advising my customer in a sense that I'm
2 going to make a sale, but of course I face the risk of
3 redundancy if I reach the same customer twice, and
4 that's something I want to avoid.

5 My ultimate advertising policy in each one of
6 these advertising markets is basically a policy which
7 tries to resolve it.

8 Now we're ready to describe the equilibrium
9 of these markets and advertising policy for a firm is
10 not to actually decide in which market it wants to be
11 present in and how many of the messages. It's what
12 volume of advertising he wants to achieve in these
13 markets.

14 And so we can say, "Well, the gross revenue
15 is simply coming from the number of matches that I can
16 generate and support by my advertising policy," and
17 what I want to resolve in my policies is basically the
18 optimal trade off.

19 With the geometric distribution, we can
20 actually solve for the demands in the competitive
21 equilibrium and we get a linear demand function, so we
22 can then trace out the impacts of a better targeting
23 technology on the markets.

24 Another nice feature of the exponential
25 distribution is that we have a certain station area

1 that the markets basically -- whether or not it is the
2 same in terms of the competition, they all look the
3 same with respect to the relative composition in each
4 of these markets, so the prices are actually equal
5 across all of these markets.

6 So what do we find? As soon as there was
7 some targeting opportunity that is much larger than
8 zero, we'll find that both small and large ones will
9 advertise. And that's a fact that we'll be presenting
10 on either the small or large market, depending on the
11 size. And so now we can ask: First of all, what is the
12 social value of targeting? What are the numbers of
13 matches that are supporting advertising technologies,
14 which have better targeting opportunities?

15 And here we find that it's uniformly
16 increasing the wealth here simply because it supports
17 more matches. The question then that we ask is: Well,
18 how was that increase in the social value supported in
19 terms of the purchases that the consumers are actually
20 making?

21 What we see is that we see a change in the
22 advertising policy in the sense that firms start to
23 purchase less volume, and it's the smaller firms which
24 take up some of the slack, so this is the long tail and
25 Anderson. But it's also going to be true that the

1 number of participating firms in each one of the
2 advertising markets is declining because in some sense
3 the interest in any particular advertising market
4 focuses on a smaller and smaller segment of firms or
5 products.

6 So that leads us to ask: As we increase the
7 value of the social technology, will the advertisers be
8 able, over the media, to cover or recover some of the
9 gains in terms of the social value of the matching in
10 terms of the price?

11 What we find here is that initially as we
12 increase the targeting possibilities, indeed the price
13 for the advertising is going up simply because we have
14 a higher value that we're offering per a message being
15 sent, but eventually then the price for each individual
16 message that I'm going to buy is going to go down in
17 the equilibrium. And the idea is here that as the
18 messages become more and more efficient, the concern of
19 the advertisers is moving away from not hitting the
20 right people to sending the same message often to the
21 same people.

22 As you move from the cost of not reaching the
23 right guys to basically the cost of saturation or
24 duplication, we will also see that the price is
25 changing and then returning as it's decreasing, even

1 though the value of the advertising technology is
2 increasing.

3 There's some interesting empirical evidence
4 in the sense that in a recent paper, Chandra and Kaiser
5 looked at the value of targeting in the magazine
6 market, and there they find that magazines that can
7 offer more homogenous readership are able to extract a
8 higher value.

9 On the other hand, if you go to the Internet
10 markets, where there is a point to be made that
11 targeting effect is already very high, Rutz and Bucklin
12 show that branded key words -- that is, key words which
13 focus even more narrowly on a particular search --
14 obtain a lower price on the search engines. And the
15 same is also true for longer key words because they are
16 also targeting finer and finer markets, for which in
17 some sense there's less interest and less competition
18 in reaching the customers.

19 This is basically the first set of results
20 that we pursued. What are the implications of targeting
21 for advertising? And the second step to take is
22 basically to ask: What happens if we move away from
23 the single homing that was implicit in the first part
24 of the paper to a world of dual homing where consumers
25 can be present both in Media 1 and Media 2? And of

1 course in our world, we're interested in whether it can
2 be present there online as well as offline.

3 So the relevant comparative study is to
4 explain what happens if the consumers spend more time,
5 hence can reach more messages on the Internet, that is
6 they've increased the presence of the consumers on the
7 Internet relative to the time they spent on the
8 traditional media.

9 So, we now have competing media to do the
10 dual homing, and we can ask: What were the prices in
11 the offline media and what are the prices in the online
12 media? What's the distribution of the consumers across
13 these two media, and what happens when consumers spend
14 more time on the Internet?

15 Clearly what we find is that will always be
16 the case, this is that only the large firms can reach a
17 large audience which will be present both offline and
18 online in terms of the advertising policy. The small
19 firm will not go into the large media. They will
20 always be trying to get into the targeted media.

21 What's more interesting is to ask: What
22 happens to the price of the offline media or the
23 revenue of the offline media when we are be moving away
24 from the offline media to the online media?

25 Here what we find is that the price that the

1 offline media can distract from the advertisers is
2 decreasing linearly in the presence of the viewers
3 online, whereas if I were to think of a second
4 competitor offline, the decrease in the price would
5 only be to the square of the presence of the
6 competitor.

7 What this then shows is that the merchants of
8 the Internet have a disproportionately large effect on
9 the revenue of the offline media in terms of their
10 advertising revenue, and that's driven by the ability
11 of the Internet to provide a higher value service in
12 terms of its targeting ability.

13 That explains some of the decline in the
14 revenue of the traditional media, and in particular
15 those traditional media which can't, by construction in
16 some instances, target as finely as the Internet, and
17 here in particular the newspaper.

18 Again there's some interesting evidence to
19 that contest, that there is indeed competition between
20 online and offline. But perhaps I should just mention
21 that here we tried to present the model that allows us
22 to think cohesively about heterogeneous consumers,
23 heterogeneous advertisers, and therefore the
24 possibility of improving targeting technologies. But of
25 course our view, say of the media, in particular, is

1 rather limited in the sense that we were only
2 interested in the revenue coming from the advertisers.

3 We might also be interested in thinking of a
4 dual market where in some sense the media has tried to
5 get revenue both from the readers as well as from the
6 advertisers. And these are logical next steps to take.
7 Thank you.

8 DR. SCOTT MORTON: Thank you.

9 DR. BALAN: So I am Dave Balan. I work here
10 at the FTC. These views are mine, not anybody else's.

11 This paper is about informative advertising,
12 and you have some consumers and some products, and it's
13 a good thing when the consumers learn about the
14 products that they might want to buy, so welfare
15 becomes pretty straightforward. It's a good thing when
16 the right people find the right price.

17 So, the authors have a whole bunch of
18 environments that they model. This is a very elaborate
19 thing. I have market in square quotes, because this is
20 the FTC, and we mean something different by markets,
21 but here we have a single advertising market and one
22 medium, so that's like a world where there are
23 newspapers, and there's only one newspaper.

24 The second one is a world where you have
25 newspapers, and then you have two media likes newspaper

1 and TV, but they're the same size. Then you have
2 newspaper and TV and they're different sizes and then
3 you have newspaper and TV, and they're different types
4 in a way that I don't have time to go into. And then
5 finally you get to online: one online, one offline, and
6 then many online media, which I think is the one that's
7 ultimately of the most interest.

8 So there are a whole bunch of parameters
9 floating around in the model. The three biggest ones I
10 think are we've got this lambda parameter, which is the
11 concentration in the market, again in square quotes.
12 When lambda is big, lots of people want a small number
13 of products. When lambda is smaller, they're a lot more
14 diffuse in what products they like.

15 Gamma is this targeting parameter that Dirk
16 was talking about, how easy it is to identify in the
17 one pole where everyone is in the same place and in the
18 other pole where exactly these kind of people are in
19 exactly this market so you know exactly where you have
20 to go to reach them.

21 And social welfare is unambiguously
22 increasing enough because this is all about matches and
23 it being a good thing when matches are made.

24 When you have the online and offline, beta is
25 the fraction of the time you spend on the Internet

1 instead of watching TV or reading the newspapers or
2 whatever.

3 Then there's a whole bunch -- and I mean a
4 whole bunch -- of comparative static exercises on
5 parameters and some others, the effects of these
6 parameters on advertising prices, advertising prices
7 per person successfully reached, who in equilibrium
8 which firm sizes advertise on which media and which
9 consumers pay attention to which media, so just a whole
10 bunch of stuff.

11 Then the comparative statics are not all
12 simple. They're like all these non-monotonicities, so
13 I'm going to try one, and I think I got it, but this is
14 λ . That's that concentration parameter and in the
15 first environment, that's one newspaper and there's
16 only one newspaper, so the simplest environment. When
17 λ is low, which means that people are diffuse in
18 which products they like, you increase λ a little
19 bit and what happens?

20 What happens is everybody who was already
21 advertising their market share -- although I don't know
22 if that word just means the base of people who are
23 potentially interested in their product -- goes up, so
24 their demand for advertising goes up. So the price goes
25 up, but if λ is already high and you make it a

1 little bit bigger, then lambda goes up. The marginal
2 firm actually has a smaller base of people who are
3 interested in this product, which seems to me the
4 demand will go down.

5 But on the other hand, a bunch of the
6 infra-marginal guys have the number of people
7 interested in their product go up, which tends to push
8 it up. But on the other hand, there's diminishing
9 returns because if you hit somebody twice, that doesn't
10 help, and the net effect of that is, when all the dust
11 settles, that it's negative.

12 This is an impressive undertaking. There's
13 just a great deal here, and the results are built up
14 step by step in this manner that was described in a
15 very appealing way. The downside -- I don't know how
16 to finesse this -- is the online versus offline results
17 are on page 28 of the 34 page paper, so I don't know
18 exactly how to handle this. And there's so many results
19 that it seems like some sort of targeting of which ones
20 y would be of value, but that's just because there's so
21 much there.

22 It's bad form for a discussant to talk about
23 the paper that they wish you wrote, but I'm going to do
24 just a little bit of that. This is about informative
25 advertising, and it's not about informative advertising

1 of prices which we know what there's lots of. You open
2 the newspaper and then you find out that products you
3 already know about are on sale.

4 This is learning about the existence of a
5 product, which surely happens. Certainly new products
6 are being introduced. That's how they get people to
7 know about them, and in the example, it wasn't in the
8 paper but it was in the presentation. Maybe a good
9 example of learning about products are these things
10 like when you like a book and then Amazon tells you a
11 book that you might also like, which definitely has the
12 flavor of informative advertising because it's really
13 something you wouldn't have otherwise known about.

14 But I hadn't thought about that before, which
15 weakens the force of this comment, but I'm really
16 somewhat skeptical of how often this is really about
17 product existence, and in the paper -- and this is a
18 model, an assumption I am showing you -- I wouldn't
19 want you to put too much weight on this. But in the
20 paper, if you don't learn about your best product, you
21 buy nothing. You don't buy the next best product that
22 you know about, so I'm skeptical of how often it is
23 that we have a world where people are at sea until they
24 see an advertisement and then it's like, "Ah-ha, now I
25 know about this thing that will bring me inner

1 happiness."

2 And moreover -- and this I was worried about,
3 as I understand it, and I could be wrong -- the model
4 says that people look at media to learn about products.
5 It's not that they look at media for content and then
6 the advertisements are piggybacked on to the contents.
7 And if I'm right about that, then the bicycles example
8 -- which I'm glad Dirk mentioned in his presentation --
9 he has this idea that there are three kinds of
10 bicycles. It's like cheap old toy bicycles, decent
11 bicycles, and serious bicyclist bicycles.

12 And the serious bicyclists might read Bicycle
13 Enthusiast Monthly and Sports Illustrated and The New
14 York Times, but a guy who just wants an okay bicycle
15 reads Sports Illustrated and The New York Times, and
16 the guys that wants a cheap bicycle will read The New
17 York Times.

18 That might be true if they were reading these
19 media for content. If they're reading these media to
20 learn about products, then I don't think the bicycle
21 enthusiast is going to read The New York Times because
22 he knows he's not going to see an advertisement for the
23 fancy bike that he's interested in The New York Times.
24 So I wasn't exactly sure what to make of that or
25 exactly how many bodies are buried there but it was a

1 concern.

2 But the biggest thing -- and this is me, and
3 you won't be the first ones to think I'm crazy, if you
4 think I am crazy -- is I think advertising is about
5 persuasion. Persuasive advertising is what it is about.

6 There is a paper that says one quarter of GDP
7 is persuasion. They did this really super cheesy
8 calculation which is not to be taken that seriously but
9 a lot, a lot, a lot of GDP is persuasion. But if I was
10 the social planner directing talent into problems --
11 and I think pretty massive amounts of talent that were
12 brought to bear on this problem -- I would redirect to
13 things related to that problem. But that said, that
14 doesn't mean this problem is not worth thinking about.

15 So a very, very rich, impressive thing,
16 carefully and logically derived; the very scale of it
17 makes it a little bit difficult to digest, and there
18 might be some tweaks that could be made in directing a
19 reader with finite time to what's most important. And
20 then this comment, which you can make of what you will.

21 Obviously you have this paper now, but I
22 think figuring out how persuasion works and what the
23 welfare implications of persuasion are is kind of where
24 it is at in advertising.

25 That's it for me.

1 DR. SCOTT MORTON: Great. Well, that sounds
2 good. We'll move to the next paper. Let's thank the
3 author and the discussant.

4 (Applause.)

5 DR. PULLER: In this session on new markets,
6 the new market I'm going to talk about is essentially
7 what happens when you allow homeowners to choose who
8 their electricity provider is. We're going to analyze
9 what happens when you allow retail choice in
10 residential electricity markets, and this is a joint
11 paper with Ali Horatacsu and Seyed Ali Madanizadeh.

12 Texas, like a variety of states, has moved
13 from one means to another means of procurement of
14 residential electricity, so from a regime where
15 everybody will buy from a regulated incumbent for a
16 regulated rate to one where you can choose your
17 providers, and those providers might have discretion as
18 to what prices they charge.

19 And a lot of the motivation for this is
20 retail competition might add value-added services or if
21 a lot of consumers are actively searching, that might
22 make the market more competitive. So the models in
23 these markets often give people the power to choose.

24 Just to give you a little hint as to what our
25 findings are going to be, we have an alternative title,

1 which we haven't quite had the guts to put in the
2 published version of the paper, but this is probably a
3 more apt title for our paper.

4 I'll give you details of how retail choice
5 works in a second, but briefly starting in January 1 of
6 2002, all residential customers in Texas were assigned
7 by default to a retailer that was basically affiliated
8 with the incumbent, and then every month consumers
9 could potentially switch around from that incumbent or
10 back to that incumbent for a variety of competitive
11 retailers.

12 What this graph does is it shows the
13 evolution of market shares over the first about four
14 years of the market. As you can see, there's a gradual
15 erosion of the market share of the incumbent. You can
16 see there are two providers that have about 15 to 20
17 percent of market share, and there are a couple of
18 smaller providers, and then a variety of actually even
19 smaller providers that I didn't even put on the graph.

20 So, here's a question for you: If you had to
21 guess just based on this figure what rates were
22 charged by the different retailers, what would you
23 guess? You would probably guess the incumbent has a
24 higher rate, and indeed that is true, but the question
25 is: How much higher? And that probably depends on

1 your perceptions of the savviness of Texas home owners.

2 So, here's the answer. This is an average
3 rate for a typical usage amount. The line in blue here
4 with the dots is the average rate for the incumbent,
5 and all the other lines are rates for a variety of
6 other competitive retailers.

7 As you can see, except for a couple of
8 months, there's at least one and sometimes more than
9 one competitive retailer that has a rate, one to one
10 and half cents, sometimes even little more than that
11 cheaper than the incumbent.

12 So this motivates us to ask why, and if you
13 aggregate this across a month or across a year, there's
14 been substantial savings there. And then why, despite
15 potential savings, does there seem to be a fair amount
16 of consumer inertia keeping customers with the
17 incumbent?

18 What are possible causes of consumer inertia?
19 We are going to try to group them into three categories
20 and then try and empirically quantify these. So the
21 first category could be that, in fact, electricity is
22 not a homogeneous product. Anecdotal evidence is that
23 people perceive that the reliability of their power is
24 a function of who their retailer is.

25 Technically that's not true at all. It's

1 still the same power, runs at the same volume, same
2 meters and everything else, but maybe people have the
3 perception that if there's a power outage, it matters
4 who their retailer is, even though it doesn't.

5 The second category could be that maybe
6 customers suffer from status quo bias, and they just
7 don't pay attention. We're going to call this decision
8 cost. And the third category is that maybe there are
9 actual switching costs. For example, non-monetary
10 switching cost might be that I have to get accustomed
11 to what a new bill looks like and change my online bill
12 pay, for example.

13 We think there are merits to trying to
14 quantify these effects, in general because these might
15 show up in other retail choice markets, but for this
16 particular case, because there could be policy
17 implications. So for example, if I think that it's kind
18 of a brand effect, maybe that will erode over time, and
19 if so, maybe you just think about that as kind of a
20 transition cost to retail competition.

21 If they're decision costs, maybe public
22 information campaigns can reduce those costs. Are they
23 switching costs? I'm not really sure if there are
24 policy levers to influence that. Maybe there are,
25 maybe there are not.

1 So the goals of this project are to quantify
2 those and to see if there's evidence of product
3 differentiation, search cost and switching cost, and
4 then also to ask the question: Are there
5 heterogeneities across different demographic groups? So
6 loosely, do different demographic groups benefit more
7 or less from having retail choice in residential
8 electricity?

9 This is related to a variety of literature,
10 works that have looked at retail choice and things that
11 are traditionally utilities, whether natural gas,
12 telecomm or electricity, but more generally to a
13 literature that looks at what happens if you take some
14 product and move from a regime where everybody has to
15 buy that product at some regulated provider -- there's
16 no choice -- to a regime where there is choice. And
17 that product could be a school. It could be health
18 insurance. It could be long distance telecomm and
19 asking what the distributional consequences are of
20 adding that choice.

21 So what I will do is just give you some basic
22 descriptive statistics that look at the raw data, and
23 we'll build a model, which is going to econometrically
24 be able to test for these three different effects,
25 sources of inertia. Basically we're going to find that

1 there is an incumbent brand advantage, but it tends to
2 erode over time.

3 We're going to see that people don't search
4 very much, but there is a seasonal pattern, which I bet
5 you guys can guess if you've ever been to Texas a
6 certain time of the year. And we're also going to find
7 that there's some demographic heterogeneity, and I'll
8 tell you what that's going to be.

9 Some of us might have personal experience
10 with retail choice. In any state that's not dark blue,
11 there's been some experimentation with choice either at
12 the residential level or the commercial and industrial
13 level.

14 The way it works in Texas starting in January
15 of 2002, is customers were assigned to a retailer that
16 was affiliated with the old incumbent, so an AREP.
17 That AREP had a required rate called the price to beat,
18 which was actually a cut from what it had been before,
19 but because of a variety of things that were going on
20 in the wholesale market, that was still thought to be
21 above competitive levels.

22 Regulators thought through some logic that
23 that was a good thing because it basically guaranteed
24 head room for retailers to enter into the market. The
25 rate could be adjusted over time, but it was adjusted

1 in a way that was indexed to cost.

2 So for the competitive retailers, these are
3 just kind of intermediaries that procure power from
4 generators and then market those to customers. It
5 turned out the largest CREPs were also AREPs from other
6 parts of the state, so brand names that were known in
7 other parts of the state. By the end of our sample
8 period, which was 2006, there were typically over ten
9 CREPs.

10 So critical for understanding why there might
11 be consumer inertia is finding out how do consumers get
12 their information, so there are media sources, as you
13 guys can probably guess. One critical website that was
14 actually created by the Public Utility Commission was
15 basically viewed as a one stop shop to learn about
16 rates and to conduct a switch.

17 Here's a screen shot of what that looks like.
18 It may be a little small, but basically what you do is
19 you type in your Zip Code, and then it will give you a
20 list of a variety of different providers and
21 characteristics which you can sort. For example, they
22 will tell you what the average rate is of a typical
23 usage level of a kilowatt hour, and it will tell you
24 what a thousand will cost, just in case you can't
25 multiply by a thousand. It will tell you what the rate

1 structure is, whether it's variable or fixed, whether
2 there's some wind energy blended into that, and what
3 the terms and cancelation fee are. Then if you want to
4 switch, you can click through and find out other
5 information and actually click through and conduct your
6 switch.

7 What we're going to look at is a certain
8 service territory which you can see in red here. It
9 was spread across the state because it was formed as a
10 result of mergers over time. It's nice for us because
11 we're going to get some nice demographic mix of urban,
12 suburban, and west Texas rural areas. We're looking at
13 the first four years of the market and about 200,000
14 customers.

15 If each of those customers were actually
16 technically metered, what we have is each month who
17 their provider was and how much they consumed that
18 month. Then we have the address of the meter so that
19 we can link that to characteristics of the census block
20 groups, not on an individual level, but census block
21 group characteristics.

22 And for each retailer, we have the rate plans
23 that were offered. So what we can do with maybe a
24 little bit of error is calculate what the bills were
25 and counterfactually what the bill would have been if

1 they had bought the same power from any of the other
2 providers. And we're going to focus on the six largest
3 retailers.

4 Just to give you a little descriptive data
5 before I go into the model, this just shows a count of
6 the number of switches for each month in our sample
7 period, so as you can see in the first year, there
8 wasn't as much switching behavior as there was in later
9 years, and if you squint but just a little bit, you can
10 see that there's a peak every year, and that peak is
11 going to correspond to June, July and August.

12 So now we described what potential savings
13 could be, and I just mean this purely as descriptive
14 evidence. We're going to ask the question: For
15 households in the months that they're buying from the
16 AREP, the incumbent, what would their bill have been if
17 they had bought the same amount of power from any of
18 the CREPs?

19 Now, this isn't a welfare calculation by any
20 means. It's not accounting for switching costs. It's
21 assuming that they forecast everything right, but it
22 will give us some idea of the magnitude of what
23 potential savings would be.

24 To do that, we're going to have to make some
25 assumption about how savvy consumers are and how often

1 they search, and we're going to have two extremes. At
2 one extreme we're going to let these guys
3 counterfactually switch only once, and they're going to
4 switch at the very beginning of retail choice to one of
5 the other big named providers, one of the big named
6 CREPs, and depending on who they switch to, it's going
7 to be somewhere around \$7.50 to about \$10.

8 At the other extreme, we're going to imagine
9 that every single month they switch to the lowest cost
10 CREP, which is technically infeasible but it will
11 provide us an upper bound, and then we're getting
12 members who are at a little over \$12.

13 So we think somewhere between 7.50 and \$12,
14 and just for basis of comparison, other energy policy
15 according to CBO would have cost each household a
16 little more than that but not that much more.

17 Finally, descriptive evidence about the
18 demographic effects. We would like to say which
19 demographic groups, or at least neighbors, might take
20 more advantage of choice, so to do that what we're
21 going to do is calculate household level metric of
22 percent achieved. We're going to calculate when they're
23 with the incumbent, what the bill is with the
24 incumbent, what the bill counterfactually would have
25 been if they had bought the same amount of power from

1 the lowest priced CREP and then what their actual bill
2 is, and then we're going to calculate this measure of
3 what percent of potential savings was actually
4 achieved.

5 So this is going to be a household-month
6 level observation where this variable is going to be
7 something between zero and one, and then we're just
8 going to regress this on census block group demographic
9 characteristics, again just descriptive analysis. Again
10 this is an individual level data, right, and there's
11 heterogeneity within a block group.

12 I encourage you to think about this more as
13 neighborhoods as opposed to individual level effects,
14 and we're seeing that there's a high percent of
15 realized savings in neighborhoods that have more
16 college educated, more African Americans, fewer
17 Hispanic, fewer seniors and a lower poverty rate.

18 Now, I'm not going to view that as a demand
19 side estimate because obviously some of these
20 demographics could be associated with things that firms
21 might do, like advertising. So I'm not necessarily
22 viewing this as the demand side, but it's still kind of
23 characterizing which neighborhoods seem to be taking
24 more advantage of choice.

25 Now let me go into the model. We're going to

1 imagine choice as every single month for households
2 engaged in a two-stage process. The first stage is
3 they're going to basically decide whether or not to
4 look around.

5 If they don't look around, they're going to
6 stay with the same provider, which we're going to call
7 Provider K. If they do look around, they're going to
8 engage in a standard discrete choice decision. They're
9 going to observe the product characteristics of the
10 alternative retailers and choose the one that maximizes
11 utility, keeping in mind that they can decide to stay
12 with their existing provider, Provider K. And when we
13 estimate this, we're going to allow for heterogeneity
14 across both the probabilities of looking around and the
15 choice probabilities.

16 One set that's going to help us with
17 identification is institutionally there's a group when
18 you move into a new house, you don't get any power
19 until you make a decision. You have to actively
20 choose, and so we're going to model these people's
21 deciding with probability one.

22 In the paper there's a formal model, but let
23 me just give you a simplified model to give you a sense
24 of how we're doing this. So, let's assume there are
25 only three retailers. Everybody is the same, and us as

1 analysts only observed two months of data, last month
2 and next month.

3 Let's assume that each household currently
4 with Retailer K is going to search with some
5 probability that is specific to that retailer, and then
6 those that decide to look around, conditioned on
7 deciding which households are going to choose the
8 Retailer J with probability $P(J)$.

9 In the simple model, we have five parameters
10 to estimate. The probability of looking around for
11 each of the three retailers, and the probabilities of
12 choice: $P(1)$, $P(2)$, and then $P(3)$ is just going to be
13 $P(1)$ minus $P(2)$. We've got five parameters we want to
14 estimate, so how can we get that?

15 What we're going to do is create a matrix
16 that's counting the number of people as a function of
17 who their last provider was in the rows and who their
18 next provider is in the columns, so since people don't
19 switch that much, the diagonals are going to be well
20 populated, and the off diagonals are going to be less
21 populated.

22 We can write down an expectation of the
23 numbers that are going to be in each of these cells.
24 Let's assume that the total number of people that have
25 been with Provider 1 is $N(1)$. In this first cell, in

1 expectation, we would see that for each individual, the
2 probability that someone doesn't decide to look around
3 plus the probability that someone does decide to look
4 around but then chooses their current utility.

5 In the second cell there is simply the
6 probability that someone that looks around times the
7 probability, conditional on looking around, and then
8 they choose Provider 2, and the same thing for number
9 three.

10 What this matrix is going to give us is nine
11 moments. Now, it turns out that in each row, one of
12 the moments is redundant, so we're only really getting
13 six, but we can use these six moments to estimate the
14 five probabilities. So in simplified terms, that's
15 basically what we're doing.

16 Now, we want to interpret these lambdas and
17 P_s , so to do that, we're going to actually parameterize
18 both of those things, the looking around function and
19 the choice function.

20 As far as the choice function, the lambda,
21 we're going to make that just a nice kind of S shaped
22 function with the variables that are going to enter
23 into a retail variable, so who the last retailer was,
24 the month of the year to allow for seasonality and
25 searching, and in some of our specifications, census

1 block group demographics.

2 And for the probability function where you
3 use a standard discrete choice set up, we're going to
4 use a logit model, where our product characteristics
5 are going to be price, a dummy for the incumbent to
6 pick up an incumbent brand advantage, that interactive
7 with months to allow for that brand effect to vary with
8 time, and then to identify switching costs, we're
9 basically going to have a product characteristic that
10 is, "I don't incur switching costs."

11 So who doesn't incur switching costs? You
12 don't incur switching costs if you're staying with the
13 same provider and you're not a mover. Now, it turns
14 out that the identification here is really coming off a
15 nonlinearity in the logit probability so it's a
16 functional form assumption. So if for some reason
17 you're not comfortable with that, we'll present results
18 not estimating switching costs and then estimating
19 switching costs.

20 We're just going to pack all this into a GMM
21 estimator. Think back to that three by three matrix; a
22 count in each of the cells is just going to be equal to
23 the probability of anybody being in that cell.

24 I'm going to show you results that are in a
25 couple tables like this. Let me be clear on what's in

1 these tables. The top two panels are parameters for
2 estimating the choice step and the decision step, so
3 it's just parameter estimates. And then based on those
4 parameters, we can calculate things that we can
5 interpret. So mainly, we can calculate the probability
6 that a customer looks around as a function of which
7 retailer they are with.

8 And then given that they're looking around,
9 they're deciding the choice probability, and then we
10 can turn and also calculate what the price elasticities
11 are.

12 What we're finding here in our basic results
13 where we're not estimating the switching costs is that,
14 in fact, there is a brand advantage, but it tends to
15 erode over time. In terms of the estimated price
16 elasticity, we're finding that the regulated incumbent
17 has fairly inelastic demand and then the smaller
18 competitive retailers have a demand elasticity estimate
19 more around five.

20 In terms of when people search -- these are
21 the dummy variables of seasonality that are entering
22 into that lambda function -- we're finding that people
23 tend to search more in the summer, particularly in
24 July, but that being said, they don't search that much.
25 Depending on the retailer, they're switching anywhere

1 from 2 percent and 5 percent of the months. No
2 estimates switching costs, which again is identified
3 off this nonlinearity in the logit probability, we're
4 finding evidence that there are non-trivial switching
5 costs.

6 We are still doing a robustness test to test
7 for the appropriateness of the model, but let me show
8 you some preliminary results where we are allowing
9 these effects to vary by demographics. We're getting
10 results that I think are at least roughly consistent
11 with those reduced form regressions I was showing you
12 before in demographic characteristics.

13 So, what we've done here is we've taken the
14 price coefficient and the incumbent brand advantage
15 coefficient and interacted that with the demographics.
16 Again we're thinking neighborhoods here and we're
17 finding that you're getting more price sensitivity in
18 neighborhoods that have more African Americans and more
19 college educated people.

20 You're getting the brand advantage being
21 lower in neighborhoods that have more seniors, more
22 African Americans and more college educated people. And
23 with the exception of the seniors, this is
24 qualitatively consistent with the reduced form results
25 that I was showing you before.

1 So conclusions: We're finding that you if
2 you entirely homogenize the product, we're getting
3 dollar figures of \$7 to \$12 left on the table per
4 month. Our model is suggesting evidence of all three of
5 those sources of consumer inertia.

6 Our next step it to do welfare calculations
7 and we're interested in thinking about this
8 incumbent-brand effect. Let's imagine that the major
9 driver of that is this perception that power is more
10 reliable, even though we all know that's not true.
11 Should that count in welfare or not? And maybe this is
12 a philosophical question.

13 We're going to show results of it both ways,
14 but the numbers are going to be very different I
15 conjecture, and I guess readers will be left to
16 interpret whether that should go into welfare
17 calculations or not.

18 Thanks.

19 DR. SCOTT MORTON: Thank you. Tim Brennan is
20 our discussant.

21 DR. BRENNAN: Thanks for inviting me here.
22 We learned this morning that disclosure is important,
23 so let me disclose four things. First, I'm an
24 antitrust person, not a consumer protection person.
25 Second, I'm a neoclassical Neanderthal, not a

1 behavioral post mori most.

2 The third is that I probably know less
3 econometrics than anybody else in the room, and the
4 fourth is that I'm over the Laibson hill, so one may
5 wonder why I'm discussing this, and I may be one of
6 those soon.

7 So overall points I want to make here:

8 First, I don't think that these results are
9 particularly surprising. I'll talk about that a little
10 bit. I think that the main thing that I took out of
11 this is the accomplishment, I guess, and the thing that
12 makes me think the most about this is how it unpacks
13 brand loyalty, switching costs, and search.

14 I want to talk a little bit about how this
15 gets framed in some of the papers today I think about.
16 Is this behavioral or is this response to cost? I'll
17 mention some policy implications -- and Steve talked
18 about this a little bit about what difference it makes
19 -- and then I want to talk about something which he
20 didn't talk about in his presentation, which is that
21 his measure of pricing was average, not marginal
22 prices, which actually he makes a big deal about in the
23 paper, and I don't disagree with that, but I wonder
24 what that means.

25 I'm going to just blast through this. As he

1 pointed out, there's been a lot of work on residential
2 electricity choices. There's lots of information on
3 reluctance to choose. I should point out that Texas,
4 which after four years had two-thirds to three-fifths
5 of the people still using the incumbent, is viewed as
6 the great success of residential choice.

7 In most places it's in the single digits in
8 the States for one reason or another, so Texas is
9 actually quite unusual in that regard. There's been
10 extensive efforts at persuasion. He talked about some
11 of those, and as we've heard a little bit earlier
12 today, the choosing not to choose is not unique to
13 electricity. I mean, how often do we change our brand
14 of toothpaste or cereal or this, that or the other? And
15 the idea that people stick with what they've got is
16 really not that unique to this.

17 Just to illustrate, this is something I think
18 I've shown here before; this is from a Pennsylvania
19 guide to help people choose their electricity provider.
20 It's a little hard to read, but it has eight little
21 tips here and things about each electricity generation
22 supplier for you to save, the price would be this,
23 multiply something on line 3 by line 4, divide the
24 subtotal.

25 Then we have a picture of a family, and we

1 can't really see it very well, but it looks like
2 they're really happy on Christmas day, opening an
3 envelope saying that Santa has given them the right to
4 choose their electricity supplier, and they're
5 delirious.

6 These are the questions to ask your
7 electricity generation supplier. This is a woman who
8 is happy, I guess just before she puts the gun in her
9 mouth, about having to ask some retailer all of these
10 things. So I think, "Why are you bothering to do this?"
11 It shouldn't be a surprise that anyone wants to bother
12 with this. Wasn't it fine before? And a lot of people
13 who aren't economists ask that about opening these
14 markets.

15 Now, part of the reason that I found this
16 paper so provocative is that if you think about
17 choosing to stick with the incumbent, there's brand
18 preference or switching costs or search costs. And it's
19 hard even for me to tell those about just thinking
20 about them, much less econometrically as
21 differentiation risk aversion or just not wanting to
22 bother.

23 Someone mentioned Schmalensee's pioneering
24 brands earlier but I think that the risk isn't
25 reliability risk. I think it's a business and price

1 risk. Here is this company that's been around for
2 decades and here's some fly by night electricity
3 provider. How do I know they're going to still be in
4 business in six months?

5 I think that's the risk, not whether there's
6 going to be an outage or not particularly. If search
7 is seeing that the new provider is as good as the old
8 in terms of being reliable in that sense, can one
9 separate brand preference from search costs? After all,
10 what you're searching is to find out if they're like
11 the incumbent or not.

12 If switching costs are low, does that reduce
13 the cost of search, at least when we're talking about
14 ex ante verification about that? As I was thinking
15 about this, I was wondering whether Steve could appear
16 in those old Miller Lite ads where people are talking
17 about the demand for Miller Lite beer where it was like
18 "More taste," "No, it's less filling," "No, it's more
19 taste," "No, it's less filling."

20 They have these arguments about it, and
21 actually it may be a career for him because I was
22 trying to Google it and see if I could find a picture
23 of an old Miller Lite ad on the Internet. I couldn't
24 find one. But I did find that Miller is going to
25 revive that ad campaign, so Steve can be sitting there

1 in the bar, and when the argument breaks out, he can go
2 up to Peyton Manning and say, "Look, I have this
3 generalized method of moments regression; it will tell
4 you whether it's more taste or less filing and how
5 much." So that's kind of how I saw this.

6 did he and his coauthors do it? I'm not sure
7 about this because I'm not sure that what he did
8 matched the simple example for reasons that I'm going
9 to indicate here.

10 I'm going to talk about the 3 by 3 matrix
11 that he had up. It looks like you have N brand
12 preference variables, and then you had the probability
13 of switching. And you had that $P(1)$ $P(2)$ there -- and
14 at least in that diagram -- that probability of
15 switching is independent from where you started from.
16 That's what gave you more moments than values and so
17 that's how that would work.

18 I wonder whether that's true in the sense
19 that if you went to somebody because they were green, I
20 might be more likely to pick an alternate green
21 provider. Someone who is making those switches just
22 may be different, and if it is different, then I'm not
23 sure that you've got the extra degrees of freedom or
24 what exactly you want to call it, to be able to pull
25 this out.

1 One of the things that I liked about this is
2 that it is an attempt to characterize this in cost or
3 preference terms. And I would take how much people are
4 losing a month by this, which is an impressively large
5 number, as basically their willingness to pay to avoid
6 being put in the position of that poor family in
7 Pennsylvania.

8 What difference does it make? It depends
9 upon the policy objective. If you're going to make
10 these markets work come hell or high water, then it
11 depends. If you think it's search, fix this. If you
12 think it's switching, fix that, and so on, like
13 unreportability in telephones for example. But if the
14 question is whether to have markets at all, it's all
15 part of the same cost basically.

16 Maybe the incumbent would be free to exploit
17 that, and someone that switched may be worse off
18 because maybe they preferred being in the regulated
19 environment. I might just say rationally, let the
20 Public Service Commission do it for me, I've got better
21 things to do, and let the 65 percent of the market,
22 commercial and industrial, make the choices as actually
23 they do.

24 Finally, just a couple things on something
25 Steve didn't talk about, so I'll be very, very brief

1 about this. He actually says -- and I don't doubt this
2 -- that the relevant price he wants to use is the
3 average price people pay, not the marginal price people
4 pay for electricity. There's a lot of data on this, and
5 actually the UCEI released a paper I think yesterday.
6 This is a common argument in electricity.

7 And it may very well be. I'm not going to
8 give some sort of neoclassical, "Wow, this is real.
9 What's going on about it, but what does it mean?" If
10 it means something like on the third bullet there,
11 looking at the fact that if price is constant, it
12 doesn't matter. But if there is some variation, if it
13 really is maximizing the value minus the average
14 revenue times output, that's value minus revenue and
15 that assumes that they're even more sophisticated,
16 which probably is not it.

17 If that's not it, then you need two
18 equations. One is that there's this price that they
19 take to be constant. The second is that price happens
20 to be equal to the average price, and the problem with
21 that is, I think, you get multiple equilibria, so I
22 don't know exactly how that plays out.

23 And part of the reason I want to know this --
24 and this is the last slide -- is to ask a question like
25 what Joe asked before, which is: I'm intrigued with

1 this average pricing idea because I don't know what to
2 do with it if I was in a market where I really thought
3 this is what people were doing. What does the SSNIP
4 mean, putting my antitrust hat back on here? What does
5 the upper pricing pressure mean? Where are the models
6 that tell us what somebody is going to do if they're in
7 an average price world? What would a monopoly do if
8 they thought its customers were acting that way?

9 I'm not exactly sure what the answers to
10 these are. Maybe if I had a little more time, I might
11 come up with something, but maybe people already have
12 answers for this, which is fine.

13 That leaves a question about how we do cost
14 benefit tests generally if the area under a demand
15 curve is based upon average rather than marginal
16 prices. What does consumer surplus mean in that
17 context? Those are some of the thoughts that occurred
18 to me reading this really great paper.

19 So thanks very much.

20 (Discussion off the record.)

21 DR. SCOTT MORTON: Thank you.

22 DR. EUGENIO MIRAVETE: This is joint work
23 with Jonathan Ketcham and Claudio Lucarelli and Chris
24 Roebuck.

25 Thanks for having this paper. It gives us a

1 great opportunity to revise it, and actually there's
2 already a new version available on my website. We're
3 going to talk about Part D.

4 Part D started in 2006. Oh, the disclaimer,
5 last time I presented this paper, it took me over two
6 hours, so 18 minutes is out of the question. Many of
7 the details are in the paper, but I won't be able to go
8 over it.

9 Participation rates are over 90 percent. Part
10 D has expanded prescription drug use and lowered out of
11 pocket drug prices, so beneficiaries are generally
12 satisfied with that. The cost of the program, which
13 exceeds about \$39 billion, is less than what initially
14 was thought.

15 So the question is: If everything is so
16 great, what is the controversy about it? So we think
17 it's whether consumers are making the right choices and
18 if choosing among many different plans is beneficial or
19 not.

20 Just to give an explanation for the title we
21 have, this is the presidential address of McFadden
22 seven days after the program was implemented, and his
23 judgment was that the program was not going to be a
24 success. He, in later papers, changed that view. A
25 few months later Krugman thought that seniors were

1 making choices among many options. They were of course
2 seeing it as very complicated.

3 Then we have Thaler and Sunstein offering the
4 explanation that people have 46 choices, and telling
5 consumers anything is like not having help at all. They
6 haven't updated this reference.

7 Another comment about health insurance, so
8 all this gives you an idea of what the initial
9 consensus in this market is. People were very
10 skeptical about consumers being able to make choices
11 that minimize the costs or direct consumption.

12 We have more evidence. All these are
13 references referred to in Medicare Part D. Many of
14 these papers are making use of the survey data. Some
15 of them are not, but in essence, they go in the
16 direction that consumers, one way or the other, are
17 making mistakes. They have some bias because they
18 place more value on certain features.

19 There's a paper by Abaluck and Gruber,
20 valuing some features like monthly fees other than the
21 prices of the drug and so on and so forth; they could
22 perhaps question where many of these things are coming
23 from a cross-section or lab. I have nothing against
24 that, but we cannot look at what is the effect of the
25 market anyway.

1 Here are some more of the papers related to
2 other industries, so on and so forth. I don't think I
3 have to go here, but we could perhaps start educating
4 ourselves when we are going to make the decision on
5 Medicare, you have to make a choice among several
6 different plans.

7 There is a total of 39 markets, and
8 essentially you have to sign up for a plan. That's in
9 those payments every month, and you get some sort of
10 discount on the drugs. The plans are very different.
11 They cover different medical conditions. They have
12 what sometimes are hated features like this donut hole,
13 so coverage stops if you go beyond about \$2,200, and
14 then restarts later on at \$5,000.

15 You can assure against them that this is
16 initially decided -- a sign to give an incentive to
17 consumers to reduce consumption or take care of
18 consumption. Now, let's try to get a little bit more
19 into what the problem is from the choice point of view.

20 So consumers, and we're talking about the
21 elderly here with cognitive problems, have to choose
22 many times between 50 different plans. The choice is
23 made at the end of the year, then there are six weeks
24 of an enrollment period, and you stick to that choice
25 for the rest of the year, except if you are a low

1 income individual. We are not looking at this in this
2 paper, if you change to different a market.

3 Some information you can gather from
4 websites, but the information about the choices in 2006
5 didn't exist that much. Then give an incentive for the
6 people to sign up for the program if you think your
7 premiums will go up 1 percent every month. This is an
8 extremely interesting obligation. It's a unique
9 opportunity. Everybody in 2006 is the same. They have
10 the same experience independently of age. So in a
11 sense we can separate what the effect of aging and
12 experience is and avoid issues like state dependence
13 and so on in terms of the estimation.

14 The next one is a big one. We go and look at
15 2006. We figure out that some people make mistakes, so
16 on and so forth. People maybe have some bias for one
17 or the other. What do we conclude about this?

18 Should we help consumers or are they
19 rationale? What kind of value do they have? These
20 decisions are repeated over time. So that opens the
21 possibility of learning and perhaps switching them into
22 different plans. Essentially this is the paper.

23 Here we have this vision of overspending. We
24 have data for 2006 and 2007. Here we have the brief
25 distribution of overpayment defined as whatever you

1 consume. Now look at the alternative, 49 different
2 plans, and let's see how much you are paying.

3 So here the mean is about \$550 in 2006.

4 UNIDENTIFIED SPEAKER: This is overpaid
5 consumption and you take the minimum?

6 DR. MIRAVETE: Yes, actual to minimum,
7 including the possibility of no insurance.

8 In 2006, we have lots of people around \$300
9 to \$500, and then the distribution obviously switches
10 in 2007. And lots of people are now in these smaller
11 confines of about a \$100.

12 This could be for a variety of reasons. You
13 could say, "Wow, it's just learning. Everybody is
14 switching, and everybody is becoming very smart." It
15 could be also the fact that the plans have been
16 changing over the years, and now there are less
17 potential gains. But the shift is still there.

18 The distributions like this, the differences
19 you can see between the mean and the media, are shown
20 by a line there. Some people actually pay a lot of
21 money, much more than other plans. So what are we
22 going to do? Well, essentially we're looking at all the
23 data we have, just trying to figure out what we can
24 learn.

25 This is unconditional of everything. And the

1 rest of the paper is pretty much looking at: Well,
2 what can we learn? Can we learn something about it?
3 Is there switching behind this? What exactly do we
4 have?

5 We have a huge data set. We are working here
6 with about 75,000 individuals. We have searched all
7 their consumption. They are in these 39 different
8 markets. Remember there are no low-income individuals
9 because they have a different regime. So, we know some
10 things. We know their age. We know gender. We have
11 information about their health status. We know what
12 drugs they are consuming, so we can figure out about 15
13 different medical conditions, and so on and so forth.

14 We use all that information. We recomputed
15 the costs of their drug consumption, and we have
16 alternative plans in each one of the markets, and we
17 can do a little bit of switching. We have one
18 opportunity to look at that. We also analyze what
19 happened with this out-of-pocket spending. We apply
20 some elasticities for the demand of drugs. We also
21 look at the case with zero elasticity. We look at many
22 of the issues.

23 So here we have some of the characteristics
24 of a plan and the plans not included in our sample, in
25 general, with a few exceptions, the plans are not very

1 different from the rest, so let's call them
2 representative.

3 In these simple regressions, when we look at
4 the magnitude of the change in overspending, the alpha
5 is the parameter we want to figure out. Here we have
6 changes in health conditions, and that's essentially
7 the effect.

8 We are getting some data around \$300, so in
9 principle just from one year to the next, the
10 individuals are going to be reducing their out of
11 pocket expenses by about \$300.

12 We run the same thing for a subset of
13 individuals with stable conditions, and what we are
14 looking at here is individuals with a very small
15 variation in this risk index. The last column of this
16 implies that there are no changes in any of the ten
17 medical conditions that we are tracking. It looks like
18 that's not relevant, so this reduction is independent
19 of whether we have stable conditions or not.

20 You're going to estimate this from the table
21 that essentially 80 percent of the people are able to
22 reduce their expenses going from 2006 to 2007. 20
23 percent go up, but this could be perhaps due to some
24 shocks or something like that, but most of the people
25 reduce it.

1 Since we have these demographics and we have
2 the information, we want to figure out, is there any
3 pattern? Can we figure out whether there are some
4 individuals that are able to take advantage more than
5 others and so on?

6 Out-of-pocket changes essentially vary with
7 demographics. Here we have the common conditions like
8 cholesterol and diabetes. They are the ones who
9 realize larger reductions in the out of pocket
10 expenses. If you look at Alzheimer's, they were not
11 very far away, so they fall actually within the bulk.

12 We are not claiming that people with
13 Alzheimer's or dementia are smarter than the rest, but
14 that we have institutions who are actually helping
15 those individuals.

16 This is something that happens; it's very
17 interesting. Another important effect in the reduction
18 happens for age groups 80 to 85 more than people of
19 about 65 to 70 or 70 to 80. 80 to 85 are actually one
20 of the groups that reduce the out-of-pocket expenses
21 more than anybody else. We have evidence that this is
22 likely because of these institutions, family, or others
23 who help them to make those choices.

24 I'm sure I'm skipping things. It's
25 impossible to go over everything here.

1 The next step we were going to look is how
2 important is switching and what people are going to
3 engage in switching? And you can see here that the top
4 two panels are the distribution of overpayments in 2006
5 and 2007 for those individuals who switch, so clearly
6 there's a switch in the distribution when we go from
7 2006 to 2007. The switch is not that important when we
8 look at individuals that don't switch.

9 Let me summarize the results that we find.
10 Most individuals are going to reduce their expenses by
11 about \$436 by switching plans. That doesn't mean that
12 individuals who switch are the only ones who save. We
13 saw individuals who did not switch plans reduce their
14 out-of-pocket expenses by \$137 on average, so
15 sometimes they're becoming less expensive. There is
16 another issue that we can address here: What is the
17 effect of inertia? We could say, "Well, I signed up
18 for this particular plan and I'm going to stay for this
19 plan forever."

20 Another thing we find is if your plan goes
21 down into the range, it becomes suddenly much more
22 expensive, you tend to move out of that plan. At least
23 that's what we find in this first year.

24 That's the effect of inertia. Health status
25 is not important, and another interesting thing we find

1 is that people who acquire a condition are e the ones
2 who would use their out-of-pocket expenses more.

3 One way to interpret this is conditions like
4 hypertension. You know that they are coming so those
5 guys actually sign up in 2006 for plans that were a
6 little more expensive than necessary, but even though
7 they didn't get their medications for hypertension in
8 2006, but they got it in 2007, and at that moment their
9 savings are much larger.

10 I think the thing we do is robustness for
11 2007, we can actually look at expected consumption,
12 taking the consumption in 2006 and see what happens,
13 and we changed the elasticities which is another thing
14 by the way.

15 DR. SCOTT MORTON: Wonderful. Thank you.

16 DR. HOADLEY: So, my disclosure is I'm a
17 political scientists here in a room full of economists,
18 and I don't know what that's worth.

19 Basically what the authors of this paper
20 start from is the premise that the Part D experience
21 has been largely positive. I'm going to test the
22 question of whether the trust environment is part of
23 the positive side of that, that we're really seeing
24 people respond well to the choice opportunity that Part
25 D creates.

1 I would just like to put a few caveats on the
2 table on challenges that are remaining, and one is that
3 we're seeing a lot of increasing premiums for
4 beneficiaries. We're seeing a lot of volatility for
5 the low income, although this paper didn't really
6 address the low income side.

7 My work suggested choices are still quite
8 confusing, and that the cover gap, the doughnut hole
9 that people face, are still huge challenges, although
10 the health reform does address the coverage gap in a
11 couple of these other things.

12 To make a few observations, just about the
13 Part D experience from how I see it related to this
14 question of whether choice is working, over the course
15 of the five years in the program, we see that
16 beneficiaries seem to stay in plans in the face of
17 significant premium increases, despite the fact that
18 the overall cost of the program has been on a fairly
19 reasonable track.

20 The average premiums that beneficiaries face
21 go up 44 percent in the first five years, another 9
22 percent projected if people don't switch for 2011. And
23 we have individual cases of plans with as much as a
24 couple hundred percent increase over the first couple
25 of years, and yet retaining fair enrollment despite

1 those very, very substantial increases.

2 We did focus groups with beneficiaries, and
3 we asked them very specifically about their experiences
4 of changing plans. Did they do research? What did
5 they do at the end of the year? What if their premium
6 goes up? And the consistent thing we keep hearing back
7 from this is that that's too confusing to do the
8 research, to even go into the question, and that they
9 have no bias toward staying put.

10 It's just not about the confusion of doing
11 the research. It's also about the comfort that we've
12 heard some talk about in some of the other papers
13 today, but just the comfort that the plan they're in,
14 the intangibles that keep people in the plan they're
15 in. They're in the AARP plan; they're in the local
16 BlueCross/BlueShield plan; they've learned how to
17 operate with that bureaucracy and they really don't
18 want to switch.

19 We've also heard that in behavior in terms of
20 dealing with the plans, if the things that would
21 typically drag you to changing plans or at least drive
22 you to try to get an exception to get your drug
23 covered, the process of making those kind of changes is
24 difficult for both the beneficiary and the physician,
25 but the temptation is to change the drug rather than

1 change the plan.

2 And of course that is one of the things that
3 is going to help them look like they're financially in
4 better shape. Sometimes those are perfectly good
5 changes. Sometimes they may be not ideal changes.

6 To the point of the confusion in the plans,
7 this was average premiums. These particular ones were
8 unweighted. They would be similar if we used weighted
9 by enrollment for what I consider the basic benefit
10 plans, and the first two buys versus the enhanced
11 plans.

12 The enhanced plans, by definition, are the
13 higher value. They have to have something that makes
14 them better than a basic plan, and yet the price for
15 those are almost identical, just a few percentage
16 points higher. When you go to a plan with coverage in
17 the doughnut hole, then you will see a huge jump in the
18 monthly premium despite the fact that it can be hard to
19 differentiate some of these plans. I could go into the
20 plan names.

21 In 2010, we have one basic plan that was
22 called Humana Enhanced and we had plans with the
23 designation value that are both in the lower cost plans
24 and the higher cost plans.

25 This is just a point of data which shows that

1 for enhanced plans, in most cases, you actually pay
2 higher copays for your drugs than you do in a basic
3 plan. Somehow this has a higher actual value, but you
4 actually pay more out of pocket for your drugs.

5 This is about the gap coverage, which mostly
6 at this point, is for generic drugs only, and all eight
7 plans on here have gap coverage. The dark bar is sort
8 of the share across that you face in the gap for a
9 basket of generic drugs.

10 As you can see, in four of the plans up
11 there, even though you have coverage in the gap, you're
12 still paying 96 percent of the cost of those generic
13 drugs in the gap, despite paying \$40 a month to get
14 coverage.

15 This analysis is only reported in the first
16 two years how many people actually did switch plans.
17 They haven't reported those numbers since then, and so
18 far I haven't seen anybody that's actually gone into
19 the claims data to actually calculate this. But if you
20 exclude the low income folks, about a million people or
21 about 7 percent switched plans after the first year,
22 and about 6 percent after the second year.

23 Again, I don't know how to judge that, as a
24 high number or a low number, but given some of the
25 volatility in this market, the number of choices out

1 there, and the number of people who appear to be paying
2 too much, you might expect that this is a really
3 vibrant market to see more switching. Although, this is
4 may be not inconsistent with some of the electrical
5 markets we saw in the last paper.

6 So the paper talked about this shift in the
7 amount of overspending, in other words, how much more
8 out-of-pocket costs are you paying in your current plan
9 compared to any of the other array of plans that you
10 could have switched into? And this overspending
11 reduced from '06 to '07. The paper asks whether that
12 reflects decisions to choose new plans or changes in
13 both available plan options, and finds that the
14 switches did a better job in reducing their
15 overspending than the non switchers.

16 I find this to be a really interesting paper,
17 and I hope it's true that we actually are seeing this
18 kind of switching. It's something that hasn't been
19 studied enough and it needs to be studied more, so I'm
20 glad to see this.

21 My concern is with the sample that we're
22 working with in that paper, because it's basically
23 working with only the plans operating under one of the
24 PBMs that operates in this market. It does include the
25 direct plans that that PBM sponsors, like Caremark

1 sponsors the Silver Script plans and they're not only
2 called the Caremark plans, and there is also a claims
3 administrator for some other set of plans.

4 I don't actually know which ones those are,
5 but what you've got is a relatively small set of the
6 overall market, and so I am wondering whether it's
7 constrained and unrepresentative set of options in that
8 market. I don't know if this really illustrates what's
9 going on in the full Part D market or what's going on
10 in this sort of sub market.

11 And a fair number of the plan switching that
12 we're looking at here are switches within the plans
13 offered by one sponsor, by Caremark. I think that's a
14 rather different switching environment than what the
15 overall marketing is allowing, which is a set of
16 choices across a number of different sponsors.

17 Now, there's a little bit of that in there,
18 but it's hard to know how much is in there. Between
19 your '06 and '07, the sample changes a bit because of
20 the new plans that that administrator takes on.

21 I won't go into this in any detail, but the
22 one point I wanted to make is that the Silver Script,
23 the basic plan in '06 versus '07 was actually an
24 exception to the overall rule, and the plan went down
25 by about a dollar in premium. And their enhanced plan

1 is actually one that went down by \$20 in premium.

2 So what you've got is a typical context of
3 choice demand here. Silver Script added a third plan
4 that year, which was a lower robust enhanced plan, and
5 had it at a cheaper price than their enhanced plan had
6 been the year before. And we could go through the rest
7 of the details on this.

8 Again, the sample does have a few other
9 samples, but since I didn't know which ones those were,
10 I couldn't compare those. So, I think, as provocative
11 as this paper is, it really does try to answer an
12 important question from the Medicare perspective and
13 obviously with broader implications for market
14 behaviors, but I think the paper does try to start
15 doing this.

16 How do you sort out what's going on with this
17 improvement that they sell? How much of this was a
18 conscious decision to research and switch plans? How
19 much of that was a choice within sponsors versus across
20 sponsors and how should we be generalizing from those
21 things? How much of this is about drug use changes
22 that people may be making across the two-year period
23 relative to formularies?

24 That's potentially a good choice to make if
25 they're making it in consultation with a doctor and

1 going to a perfectly good substitute drug. It could be
2 a not ideal choice for some other instances where
3 you're bringing your numbers more in line in terms of
4 this overspending.

5 And how are the results in plans changing?
6 Some of those premium differences I showed you on the
7 previous screen are some of the cost sharing
8 differences that you're passively accepting because
9 your plan is making choices. The theories put that
10 question as one of the things out there.

11 But before we draw as many conclusions about
12 what's going to happen in this market, I think we
13 really need to understand that. Secondly I think we
14 need to think about whether these results are unique to
15 the '06-07 period.

16 There was a lot of shake out in the market.
17 A lot of plans like this one came in with not very well
18 designed premiums, perhaps not well defined benefits
19 overall, and were making adjustments from year one to
20 year two. They are continuing to make those adjustments
21 every year, but knowing there's this kind of separation
22 in the first two years.

23 And I'm wondering how the same kind of
24 analysis would look if we were looking at '06 versus
25 '08 or '09 or even just the years from '06 to '08 or

1 '08 to '09. Finally, the results would vary if we
2 looked at a variable set of plans or plans within
3 different sponsors.

4 I'll stop it there.

5 DR. SCOTT MORTON: Thank you very much. Do
6 the authors want to make any comments about their
7 discussants' response or things they omitted to say
8 when they this the microphone? OK. Everybody is happy.

9 (Discussion off the record.)

10 (Applause.)

11 (Whereupon, at 5:26 p.m. the conference was
12 adjourned.)

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