

1

2

3

4

5

6

7

8

FEDERAL TRADE COMMISSION

9

SPRING PRIVACY SERIES

10

ALTERNATIVE SCORING PRODUCTS

11

12

MARCH 19, 2014

13

14

15

16

17

18

19

20 Federal Trade Commission

21 601 New Jersey Avenue, N.W., Conference Center

22 Washington, DC

23

24 Reported By: Stephanie Gilley

25

1	FEDERAL TRADE COMMISSION	
2	I N D E X	
3		
4	Session	Page
5	Welcome	3
6	Overview of Predictive Analytics	
7	Claudia Perlich	7
8	Panel Discussion	19
9	Emerging Trends in Online Pricing	
10	Ashkan Soltani	59
11	Panel Discussion	69
12		
13		
14		
15		
16		
17		
18		
19		
20		
21		
22		
23		
24		
25		

1 W E L C O M E

2 MS. ARIAS: Hi, everyone, and welcome. Thank
3 you so much for joining us to the second installment in
4 our spring privacy series.

5 Today we are going to be talking about
6 alternative scoring products, but before we begin, we
7 have some small administrative and security issues that
8 we have to cover before we begin.

9 All right. So please note that anyone who
10 goes outside today without an FTC badge will need to go
11 through the magnetometer and the x-ray machine again
12 prior to reentry into the conference center.

13 In the event of a fire or evacuation of the
14 building, please leave the building in an orderly
15 fashion. Once outside the building, you need to orient
16 yourself to New Jersey Avenue. So across from the FTC
17 is Georgetown Law Center, look to the right front
18 sidewalk. You need to check in with the person
19 accounting for everyone in the conference rooms there.

20 In the event that it's safer to remain
21 inside, you will be told to go where inside the
22 building, so just listen for an announcement. If you
23 spot suspicious activity, please alert security.
24 Security is right outside, where you came in.

25 This event may be photographed, videotaped,

1 webcast, or otherwise recorded, so by participating in
2 this event, you are agreeing that your image and
3 anything you say or submit may be posted definitely at
4 FTC.gov or one of the Commission's publicly available
5 social media sites.

6 All right. So to submit questions today
7 while the event is happening, question cards are
8 outside, available right on the table where you came
9 in. So if you want, just go ahead and grab one and
10 write your question and then we will have one of our
11 fabulous paralegals here at the FTC walk around and
12 collect them and bring them up to us and then we'll ask
13 the questions to our fabulous panel coming up.

14 For those of you participating via webcast,
15 you can email your questions to
16 alternativescores@FTC.gov, Tweet it to #FTCPriv, or
17 post it to the FTC's Facebook page in the Workshop
18 Status thread. Please understand that we may not be
19 able to get to all your questions today, but we will
20 definitely try.

21 MS. ARMSTRONG: I'm Katherine Armstrong and
22 thank you for coming here today and thank you to our
23 panel.

24 There's a lot of buzz these days about data
25 brokers and alternative scores that are used to predict

1 consumer behavior, such as the likelihood that a person
2 will be interested in a specific product or service or
3 that a particular transaction could result in fraud,
4 but we want to try to get past the buzz today.

5 And so we have a panel of experts with
6 different perspectives, different experiences, and our
7 goal is to learn more about what is happening in the
8 alternative scoring space, what may be on the horizon,
9 and the privacy and consumer rights concerns that
10 these products may raise. Our focus today is on
11 non-FCRA covered products, although we do know there is
12 a robust conversation to happen there.

13 Before we introduce our panel and start the
14 conversation, however, Claudia Perlich will give us an
15 overview of predictive analytics. Basically, a
16 high-level, nuts-and-bolts presentation about how scores
17 are created. After that, we would like to spend the
18 first half of our time discussing the various kinds of
19 products available, their uses and accuracy issues.

20 Then, Ashkan Soltani will give us a brief
21 presentation about the trends in online pricing. And
22 then, the second half, we will focus on the issues
23 involving privacy, future uses, and the regulatory
24 landscape.

25 But first let me introduce Claudia Perlich,

1 who is the chief scientist at Dstillery and
2 concentrates on data analytics for companies,
3 real-world applications, and she also teaches data
4 mining for business intelligence at the NYU Stern MBA
5 program. Claudia?

6

7

8

9

10

11

12

13

14

15

16

17

18

19

20

21

22

23

24

25

1 OVERVIEW OF PREDICTIVE ANALYTICS

2 MS. PERLICH: Thank you very much. So thanks
3 for having me here. It's a slightly different audience
4 from who I usually talk to.

5 So I'm trying to get to the basics of the
6 technology of predictive modeling and I have a couple
7 of examples of that. So ultimately, what it means when
8 we're talking about predictive modeling that's
9 underlying a lot of the questions you're interested in,
10 is algorithms that learn from data.

11 So you just give it the data and you let the
12 computer do its thing and it comes back with,
13 ultimately, models that affect your everyday life in
14 some way.

15 I've picked two examples specifically to kind
16 of explain initially how that works, and my first
17 example is Lending Club. It's a microloan site where
18 you can apply for loans and where investors can go and
19 choose what loans they want to fund based on the
20 information provided. And they actually provide the
21 data, and I want to take this, initially, to just give
22 you a very high-level overview of what might be
23 happening under the hood here.

24 So let's just look at a simple example of
25 loan default. Let's say I want to predict the

1 probability of loan default. I can do that in order to
2 make decisions whether or not to invest, I can do that
3 in order to decide what interest rate is appropriate, I
4 can even do that in order to increase the probability
5 of my loan getting funded. There are many different
6 reasons why I may want to know that.

7 So let's look at this. This is data where I
8 just give you two variables here. One is the age of
9 the person applying and the second one is the income.
10 Now, I also have historical outcomes. That's key for
11 all of this technology, that you actually need to have
12 observed some of these things and what happened.

13 So let's say for those loans, we actually
14 know who defaulted and who didn't. What happens next
15 is, I give it to the algorithm. And I'm just showing
16 it to you here in two dimensions to keep it simple.
17 You look at this information and you have those people
18 who defaulted and those who didn't.

19 What the algorithm is trying to do, without
20 any human intervention, is can it explain the data.
21 Can it find out what's different about the loans that
22 defaulted versus those that didn't. And one technique,
23 called decision trees, starts splitting the data along
24 different dimensions.

25 And the first thing it might see is, well, if

1 you look at the income, it says balance here, that's a
2 clear separation that already gets a lot of the same on
3 one side versus the other. And then it continues to do
4 that by asking those kind of questions, how do I split
5 it. Again, all of this is done automatically. There
6 is an algorithm that does it, that tries all the
7 different ways of splitting, evaluates which ones have
8 more defaults in a clean bucket versus not, and goes
9 ahead.

10 Now, at the end of this, this is called a
11 classification tree, what can you do with it? Well,
12 you can ask for a new applicant, what the tree thinks
13 the most likely outcome is going to be. And the tree
14 will just fit it into the bucket and it will say it
15 fell there, and therefore the probability of default,
16 given what it has seen so far, is roughly four out of
17 seven.

18 So that's just one algorithm that uses data
19 that you can then translate into a model. And you can
20 ask it for a new case, where you don't know the outcome
21 yet, what the model thinks is the most likely scenario.

22 A similar example here, it's a different
23 algorithm that does the same thing. So the one thing
24 to know, it's not like one algorithm we're talking
25 about. There are hundreds of them out there and often

1 they are just slightly different from each other. It
2 does the same thing, except that it doesn't try to
3 split the data, but it's trying to find a line that
4 optimally separates them.

5 Ultimately, what it means mathematically, and
6 that's the only equation I'm going to bother you with
7 here, is it's trying to estimate these betas that you
8 see there. So once you know the betas, and it's not
9 moving forward here, if you estimate the betas, you can
10 then ask the equation, what does this model think is
11 the most likely probability of default.

12 So the takeaway here is, we use data where we
13 have historical outcomes to build models that then we
14 can ask, when we don't know the outcome yet, what is
15 the most likely scenario. Now, one thing I wanted to
16 make clear here, this is a version where you see it,
17 the model doesn't understand what the axis means. The
18 model doesn't know that what one is H, it doesn't know
19 that the other one is income. The computer actually
20 doesn't care whatsoever, it's completely agnostic about
21 what is going on underneath. It just solves the one
22 question I ask it, what is the best separation you can
23 come up with and I have to specify best in some way.

24 Now, let's look at the Lending Club data that
25 is publicly available. You can go there and download

1 the information, if you want to. And they have a lot
2 of information up on the website, including the textural
3 description of the loan, categories, demographic
4 information, in addition to credit scores. All of that
5 is available, if I wanted to build this model. And
6 here is the pull I did yesterday, so you can get that
7 data. It doesn't have names in there, but it does have
8 zip codes of where the person is from.

9 Now, I want to move on to what I do, that's
10 my day job here, we're talking now about targeted
11 online display advertising. So it's about all these
12 pesky little ads showing up whenever you're surfing the
13 internet, all over the place, trying to make you buy
14 stuff. What is the data and how does this work?

15 So this is me and my company. And if you are
16 browsing the internet, and you don't have third-party
17 cookies disabled, and whoever wants to know the
18 technical details, I'd be happy to talk about this
19 later on, what happens is you will come to certain
20 sites that have data partnerships with many, many, many
21 constituents, including us. What happens, for
22 instance, if you read a blog, if we have that data
23 partnership, there is a forwarding of that and we can
24 put a cookie on your computer.

25 Now, there is a lot of misunderstanding of

1 what a cookie actually is and I'll talk a little bit
2 about what that cookie does. It basically just
3 contains a 20-digit random number that we have
4 assigned to you. The moment you delete your cookies,
5 it's gone. If you disable third-party cookies, it
6 never even gets to your computer. If you have it
7 enabled, then I can put this little piece of
8 information that is just stored. It's not a program,
9 it's just a piece of information that I store on your
10 computer.

11 Now, what happens next? We are running
12 campaigns on behalf of marketers, so marketers have an
13 agreement with us. They come to us and say, we would
14 like you to show ads, display ads, on the internet on
15 our behalf for our product. The first thing we will
16 do, we will put another one of these pixels on the
17 homepage of that brand, so now we also see who actually
18 buys that stuff. So we'll see people who go to that
19 brand's homepage.

20 One important thing is, I don't see what
21 Amazon knows about you, I don't see what you do on
22 eBay, I don't see what you do on Facebook. I get a
23 very partial view of what you do through these data
24 partnerships and it's very, very far from complete.

25 Now, once I have that, let's move on to the

1 part where the actual display advertising happens. You
2 continue surfing the internet and you get to a page
3 that actually has space for a display ad. At this
4 point, there will be a realtime auction through an ad
5 exchange. As the page loads, the different
6 placeholders for advertising are sold in realtime,
7 through an auction. We are getting bid requests. So
8 the publisher, say New York Times, forwards the bid
9 request to the ad exchange, the ad exchange sends it to
10 us, and many, many, many like us. There is not just
11 one ad exchange, there are probably 20 or 50 of them.
12 We have 30 milliseconds to decide whether or not we
13 want to bid on the opportunity to show the ad.

14 The important thing here is, what I do know
15 at the moment is that same 20-digit random number that
16 I assigned your cookie, if you deleted it, I don't know
17 it anymore, but -- so I don't know who you are, but I
18 know you are the same you you used to be when I saw you
19 before.

20 I make my choice, I bid, and if I win, I get
21 to show the ad on behalf of one of the 300-plus
22 marketers who are working with us. After that, we are
23 basically looking for post-view conversion. So we are
24 not looking who is clicking on that stuff, but we
25 actually want to see, is the person afterwards going to

1 go to that brand's homepage to either buy it or at
2 least check out the product.

3 So that's kind of, on a very high-level, and
4 not talking about a lot of technical details, how that
5 thing works. The predictive modeling piece that we
6 talked about comes in many different places. The
7 core question I have to answer is, who is even
8 interested in that brand or in running shoes or in dog
9 food?

10 So the first question is, can I build a model
11 that predicts how likely it is that you are a runner in
12 the first place, how likely it is that you are
13 interested in dog food? So that's the first piece I
14 need to solve, but there are many more. There is when
15 should I advertise, how much should I bid. By the way,
16 the creative, I have no control over. The brand just
17 gives me that thing and says that's what you have to
18 show, so that doesn't fall into my responsibility here.

19 A good question is, do these ads actually do
20 anything. We can also decide what data we need, what
21 data we buy, because we actually have to pay for that,
22 what is the quality of data, and there is this notion
23 of attribution that is more about kind of the cost
24 incentives on the other side.

25 So there are many problems that ultimately

1 rely on predictive modeling to be answered just alone
2 and in this one application.

3 We also have issues around fraud, trying to decide
4 which of these bid requests are real people as compared
5 to bots posing as people and kind of malware systems
6 that overtake people's computers, posing as them, when
7 in reality the person may actually be doing something
8 completely different.

9 What I want to highlight here is what is the
10 data we actually see and collect, because that's
11 important in the discussion you're having. So
12 ultimately, what I see is a partial browsing history of
13 you, only from those data partnerships and also from
14 the bid requests. I'm not interested in understanding
15 what you're reading on the internet, I couldn't care
16 less. I'm going to take the URL that you go to and I
17 hash it into a random string.

18 So you see, on the right side of the slide,
19 there are two parts. There is the browsing history,
20 it's kind of a timeline of hashed URLs. You have a
21 random number that is kind of your ID that means
22 nothing to anybody but me, because I use it to kind of
23 append things to your history. And I also get, from
24 the brands that we work with, these kind of purchase
25 events. When you actually went to buy a product from

1 one of the brands that we work with, because that's the
2 thing I need to predict, right? That's ultimately what
3 I'm interested in.

4 Now, the interesting point here, I do not want
5 to understand you. I don't care to know who you are
6 and what you do. I don't want any PI information for
7 that. It's purely agnostic and translated into something
8 that machines can work with that nobody else really
9 gets to.

10 Now what happens next, when I showed you a
11 model that I estimated in two dimensions, I am now
12 going to do the exact same thing, but in 10 million
13 dimensions. Every single URL is kind of its own
14 dimension, did you go there or not. And we have
15 roughly on the order of 10 million of these URLs that
16 see over the period of time.

17 So I'm building this model for every single
18 product that we are advertising to for the marketer and
19 then I use it to score people. What means scoring
20 people is, again, I see a cookie coming in, I look at
21 the history I have observed. For that cookie ID, the
22 20-digit numbers, I estimate -- I ask the model what it
23 tells me, it gives me a probability. Once you reach a
24 certain highlevel, you become the target bucket. And
25 whenever anybody from that top tier, typically it's

1 like one percent, comes in a bid request, we decide to
2 bid for that person. This is then downhill.

3 So I just have a short list here in terms of
4 all the different places where this is happening. Spam
5 has been doing this for a very, very long time.
6 There's a lot of fraud and fraud detection, financial
7 trading industry, a lot of work on this in medical
8 diagnosis and quality control, sentiment analysis for
9 blogs works exactly the same way. You look at the text
10 and try to decide is this a happy or an unhappy person, or
11 is that text from a happy or unhappy person, and many,
12 many more, one of them being advertising and targeting.

13 I'll skip the next slide, because I think
14 we'll just -- well, I guess the point, from my
15 perspective here, it actually doesn't matter that much
16 what the exact algorithm is. There are almost all
17 kinds of equivalents, some work better sometimes, but
18 at the end of the day, any of them will, more or less,
19 do the same thing.

20 What matters much more is the data you feed
21 it. The behavior of the model can only be explained if
22 you understand the data that went in to determine that
23 function. The algorithm itself is just a translator,
24 if you want.

25 Quality control is incredibly hard. If you

1 ask me how good my model is, I have no idea and I built
2 it. I don't know whether working with it another week
3 will improve performance by 1 percent or 10 percent, I
4 don't know that either. So at the end, that's kind of
5 my skill and intuition. You have this problem where
6 models really are the skill of the person who assembled
7 the data, and that's only as good as it is.

8 And finally, it is extremely difficult to
9 understand the nuts-and-bolts of what the data is and how
10 it affects the outcome. It's a really complicated
11 problem, even for people who do that for a living. And
12 with that, I'll leave it.

13

14

15

16

17

18

19

20

21

22

23

24

25

1 PANEL DISCUSSION

2 MS. ARIAS: Great. Thank you, Claudia.

3 Wasn't that a fantastic presentation? Yeah.

4 All right. So before we begin, I would like
5 to introduce everybody on our panel. We have a very,
6 very long list of panelists, so I obviously will not be
7 able to cover their fabulous information, okay? But I
8 will try to briefly give you an overview of what they
9 do. And make sure you look at the agendas that are
10 behind -- you have the bios of everybody behind the
11 agenda and so you can take a look at their fabulous,
12 fabulous history.

13 All right. So first, next to Katherine, we
14 have Rachel Thomas. Rachel is the Executive Director
15 of the Data-Driven Marketing Institute and Vice
16 President of Government Affairs for the Direct
17 Marketing Association. She not only conducts
18 independent academic research regarding how the
19 responsible use of consumer data shapes industry and
20 society, but she also represents the data-driven
21 marketing community's policy-making interests on
22 Capitol Hill. Thank you for being here with us today.

23 MS. THOMAS: Thanks for having me.

24 MS. ARIAS: Next, we have Stuart Pratt.

25 Stuart is the President and CEO of the Consumer Data

1 Industry Association. He not only represents
2 businesses that provide companies with the data and
3 analytical tools necessary to manage risk, but he also
4 has advised U.S. Presidential and Gubernatorial task
5 forces on the importance of the freeflow of
6 information to the U.S. economy and he testifies
7 regularly before Congress. Thank you for being with us
8 today.

9 Next to Stuart we have Ed Mierzwinski. Ed is
10 the Consumer Program Director and Senior Fellow at the
11 U.S. Public Interest Research Group. He often lectures
12 and testifies before Congress on a wide range of
13 consumer issues, including privacy, and he recently
14 published a law review article on alternative scoring
15 products through the Suffolk Law Review. Thank you,
16 Ed, for being with us today.

17 Following Ed we have Pamela Dixon. Pam is
18 the founder of the World Privacy Forum. She not only
19 has written numerous studies on privacy, but she also
20 has testified before Congress and Federal agencies on
21 these issues. She has a study on alternative scoring
22 coming out very soon, I've been told, so make sure you
23 keep checking out the World Privacy Forum's website.
24 Thank you for being with us, Pam.

25 Following Pam, we have Joseph Turow. Joe is

1 the Robert Lewis Shayon Professor of Communication at
2 the University of Pennsylvania's Annenberg School for
3 Communication and he has published multiple books and
4 articles relating to mass media industries. Thank you,
5 Joe, for being with us today.

6 Next, we have Claudia Perlich, who we
7 introduced before. And she gave us that fabulous
8 presentation to start us off today. Thank you for
9 being with us, Claudia.

10 And finally, to complete this very great
11 panel, we have Ashkan Soltani, who will be giving us a
12 presentation later on today. Ashkan is an independent
13 researcher and consultant focused on privacy, security,
14 and behavioral economics. He previously worked here at
15 the Federal Trade Commission and he was the primary
16 technical consultant on the Wall Street Journal's "What
17 They Know" investigative series. Thanks for being with
18 us today.

19 All right. So with that, let's go ahead and
20 begin. And I would like to start today with Rachel and
21 Stuart. Why don't you tell us a little bit about the
22 history of these products. How exactly did they come
23 about, alternative scoring products?

24 MS. THOMAS: You want me to start?

25 MS. ARIAS: Sure.

1 MS. THOMAS: Okay. Can you guys hear me?

2 Are these on?

3 MS. ARIAS: Yes, if you -- I'd like to remind
4 everybody to make sure you speak into the microphones.
5 I know they're a little sensitive, but otherwise the
6 folks in the webcast won't be able to hear us.

7 MS. THOMAS: Great. Thank you, Andi and
8 Katherine, and good morning. Lovely to see all of your
9 faces.

10 So I'm going to talk about marketing
11 analytics, predictive analytics, similar to what
12 Claudia introduced to us, because that's really a much
13 better term to describe really what's going on in the
14 marketing world.

15 So let's start with, the goal of marketing in
16 every case is to meet consumers where they are with an
17 offer for a product or a service or a cause that they
18 might be interested in that is going to be of interest
19 to them. So predictive analytics, no surprise, predict
20 a consumer's likelihood or propensity to be interested
21 in that particular product or service. That's the
22 goal.

23 Now, of course, everybody here knows everybody
24 gets marketing offers. The difference with predictive
25 analytics is that those offers are more likely to be

1 actually valuable to the consumer or the donor or the
2 potential voter. So a consumer's propensity, of
3 course, to buy a particular item is always changing.
4 If I bought a car yesterday, I'm probably not going to
5 buy one tomorrow. So those predictions about the
6 future are constantly changing as well.

7 So what markers are interested in always is
8 that extremely dynamic set of interests that a consumer
9 has from day-to-day. Not just at any given point, but
10 also in the different contexts, whether online or in a
11 store, et cetera.

12 Now, it's important to recognize -- Claudia
13 talked about the latest-and-greatest, but businesses
14 and others have been using predictive analytics for
15 more than a hundred years. Back in 1888, when Sears
16 was getting started with their first catalog, they made
17 the very smart prediction that folks living out in the
18 rural west were going to be more interested in a
19 catalog of consumer products than folks that had access
20 to a lot of stores nearby and could walk in and buy
21 them themselves. So they focused their marketing in
22 the rural west, instead of those of us hanging out on
23 the east coast.

24 Similarly, in 1912, L.L. Bean made another
25 smart prediction that folks who had hunting licenses in

1 Maine, but lived outside of the state of Maine, were
2 probably going to be interested in a catalog with
3 hunting goods in it. And so again, that was how L.L.
4 Bean got started, with a very smart prediction and the
5 purchase of a list of folks with out-of-state hunting
6 licenses from the state of Maine.

7 So fast-forwarding back to today, Microsoft
8 had some really interesting research that came out just
9 a few months ago talking about how, in asking consumers
10 what they're looking for, they want more
11 personalization, not less. Not just in the offers they
12 get, but a seamless experience, whether they're in a
13 store, or on an online site, or even in a mobile
14 version of a retailer's site. They want to be
15 understood throughout that whole purchase journey.
16 They don't want gaps between all of those experiences.

17 So to meet those kinds of fast-moving and
18 very personalized expectations that consumers have,
19 marketers use those predictive analytics to make sure
20 that they meet the customer wherever he or she is, with
21 what they're most interested in, and however they're
22 most interested in engaging. Whatever different
23 context.

24 So for example, today in a department store,
25 the store might look at what a customer has bought in

1 the past, different products from different departments
2 of that store, and look at its larger purchase history
3 to say what other customers have bought those products
4 and been interested in other things that a customer
5 hasn't yet purchased. So they are going to analyze
6 that and compare and, using those predictive analytics,
7 they're going to guess. They are going to guess
8 whether you were more likely to be interested in the
9 coupon for the jewelry department or the kitchen
10 appliances department, because maybe you bought that
11 car and now it's time for a refrigerator, or apparel,
12 et cetera, et cetera, et cetera. So that's business.

13 Nonprofits, you may or may not realize, use
14 very, very important uses of predictive analytics to
15 keep fundraising costs down by focusing on the people
16 most likely to donate. But also to hone in on
17 populations in greatest need of assistance and tailor
18 their outreach to those populations, to make sure that
19 they're most easily able to engage those in greatest
20 need.

21 The Humane Society and World Vision recently
22 have upped their ante in terms of targeted fundraising.
23 They have actually created statistical profiles, not
24 dissimilar to what Claudia was talking about, of their
25 major donors so that they can then go out in the

1 marketplace and look for others that fit those profiles
2 of folks likely to make large donations to their
3 organizations.

4 Political campaigns as well, incredibly
5 important users of predictive analytics, to target
6 political advertisements, whether in the mail, online,
7 in realtime. Pandora has a great new service coming
8 out that will let candidates or political organizations
9 target those of us who spend our days with Pandora on
10 in the background as we're working on whatever, this
11 and that.

12 So how are they going to do that? They're
13 going to look at public data of who won what elections,
14 in terms of candidates in different zip codes. And
15 then, you know, when you sign in to Pandora, you put in
16 your zip code, they are going to see who listens to
17 what music in those zip codes. So when a song that has
18 been identified as, perhaps, making a correlation to an
19 interest in a particular party comes on, you're going
20 to get an ad for that candidate or that party as well.
21 It's as simple as that.

22 So in all these cases, the organization is
23 looking at, it's analyzing information that it already
24 has about its customer or its donor or its voter to
25 understand and make a best guess to predict what else

1 that individual is likely to be interested in.
2 Sometimes they can make these often, they can make
3 these predictions just by analyzing the information
4 that they have themselves, maybe having third-parties
5 help them with the analytical power, like Claudia's
6 company and others do.

7 Sometimes they might need additional
8 information in order to make that leap to the next type
9 of prediction. So they might go to a third party, a
10 marketing information service provider, some sort of a
11 company, who can help them with the analysis and with
12 additional information to figure out what that customer
13 might want next.

14 So predictive analytics are important, not
15 just for keeping your existing customers and donors
16 happy, but for finding prospective customers and donors
17 and voters as well.

18 So if a company, for example, knows that
19 customers are most likely to buy navy blue suits if
20 they are women of a certain age in a large urban area.
21 So if they know that, they might go to a marketing
22 information service provider and say, the women who
23 like the navy blue suits, what else are those folks
24 fitting in that demographic likely to buy. And they're
25 going to find out that a pair of nude heels,

1 nude-colored heels, is going to be the perfect thing to go
2 with that suit. And they should serve a coupon for
3 that, instead of a purple set of shoes, for example.
4 So very important decisions affecting our daily lives.
5 Mine, at least.

6 So some of you may be asking yourselves, what
7 is new here? This isn't surprising, or maybe it is,
8 but what's new? The predictive analytics obviously are
9 not new. As Claudia rightly described, what's new is
10 the analytic technology that helps get the predictions
11 right. What's new is the power to actually get it
12 right and give an offer that is of interest to you, as
13 opposed to the person next to you.

14 So taking a step back again, whether this is
15 your bread-and-butter, whether this seems shocking or
16 magical or completely mundane, at the bottom line, it's
17 really important to remember what this is all being
18 used to accomplish, relevant marketing. And that's it.
19 This is marketing data being used only for marketing
20 purposes, and I'm happy to talk more later about how
21 DMA makes sure that that's true, to predict the
22 likelihood of a consumer being interested in a certain
23 product or service over another.

24 Marketing data is not used to determine that
25 individual's eligibility to receive a product, like a

1 financial product or an insurance product, and it's
2 certainly not used in any other kind of eligibility
3 decision either.

4 So at the end of the day, for better or for
5 worse, the biggest impact that marketing analytics will
6 have on a consumer's life is whether or not that
7 individual gets an ad or an offer that is relevant to
8 her interests or one that is not. And we would argue
9 that the proof that predictive analytics are valuable
10 to consumers is in the consumer reaction when they do
11 get a relevant ad.

12 Andi mentioned the research that I worked
13 with folks at Harvard and Columbia on, on looking at
14 the value of data. And in this area of marketing
15 analytics and the flow of marketing data, we found
16 that, in 2012 alone, \$156 billion were added to
17 the U.S. economy, 675,000 jobs in the U.S. alone, and
18 70 percent of that value was derived by that flow of
19 data being used for analytics between first and
20 third parties in responsible ways.

21 So we would argue that that's a value worth
22 preserving and one that is incredibly important to
23 getting it right for customers.

24 MS. ARIAS: Before we go and jump maybe into
25 what Stu and Pam may want to say --

1 MS. THOMAS: Sure.

2 MS. ARIAS: -- about the uses, I wanted to
3 give Stu an opportunity to maybe talk about other uses,
4 besides just marketing, that these alternative scores
5 or predictive analytics are being used for.

6 MR. PRATT: Okay. Well first of all, thank
7 you all for inviting CDIA to be on the panel. It is
8 good to be here. I like the word fabulous. I've
9 decided I'm going to use that in some of my other
10 presentations.

11 MS. ARIAS: You are fabulous.

12 MR. PRATT: And Ed and I always feel -- you
13 know, we're on a lot of panels together. So Ed, I
14 think in the future, that will be our theme, fabulous.

15 MR. MIERZWINSKI: And I'm fabulous. But
16 note, I'm to his left.

17 MR. PRATT: Right. And appropriately so, I
18 think. So even the seating charts are worked out just
19 right.

20 So I'm precocious. My family would disagree,
21 and I say it often to them, I'm precocious, and they
22 continue to ignore that, particularly my sons. But I
23 didn't realize that I was a big data analytics guy when
24 I was a child, so I want you to know this.

25 I lived overseas and the only way that we

1 knew what we wanted was when we waited for the catalogs
2 from the United States to arrive in the 1960s at our
3 house. And so our parents, one year, asked my brother
4 and me, well, what do you want for Christmas? And we
5 decided the best way to present our wants, our many
6 wants, many, many wants, was to tear pages out of the
7 catalogs from the various retailers.

8 And then Jim and I actually went into their
9 bedroom and taped them to the ceiling of their bedroom.
10 So that was just-in-time advertising, delivered at just
11 the right time, with big data analytics, right down to
12 the level of our needs, so that our parents could meet
13 our needs in a way that they otherwise wouldn't have
14 been able to do so.

15 So I just want you to know that big data has
16 been around a long time, including in this very
17 sophisticated way that my brother and I pioneered many
18 years ago. If only I had known that, I probably
19 wouldn't be working here today, I'd be retired on some
20 coast and looking at oceans.

21 So we're -- CDIA, Consumer Data Industry
22 Association, we really work with another part of U.S.
23 dataflows. We work with companies that are aggregating
24 data to manage risk. And risk matters, it matters a
25 lot. At one time -- I used to have a harder time

1 convincing folks of this, but if you just say two
2 words, Great Recession, we all kind of get it. Risk
3 matters, in a lot of different ways.

4 In the 1990s, risk was mostly focused on what
5 we call prudential risk, you know, how do you make a
6 lending decision, how do you make sure that banks are
7 safe and sound. But most folks shrugged their
8 shoulders and said banks are always going to be safe
9 and sound. They all seem to be doing pretty well,
10 bricks-and-mortar looks okay. But in the late
11 '90s, we began to see identity theft cycle up and
12 we realized there were different risks, risks that had
13 to do with whether or not we actually knew the consumer
14 with whom we were doing business. And because of the
15 internet, which really was something that began for
16 most of corporate America in, you know, the early
17 1990s, flowing into the next millennium, it began to
18 also be many, many more transactions that were
19 essentially where the consumer was remote to the
20 transaction. They didn't know who that consumer was.

21 So my job here today is a little bit complex
22 though, because the majority of the transactions we
23 talk about, the majority of the dataflows that we
24 represent, are regulated under a variety of different
25 laws. And Katherine has assured me that I'll get

1 pulled off the panel if I spend too much time talking
2 about all those laws, but I'm going to do that just a
3 little bit, just a little bit.

4 But our members' dataflows do a couple of
5 things really well. They encourage competition, for us
6 as consumers. And that's good for us as consumers,
7 more offers, different offers. It gives us a chance to
8 evaluate different offers. Those offers can be at our
9 desktop, those offers can be delivered in a variety of
10 different ways.

11 It also -- our data is really a framework of
12 safety wrapped around the U.S. economy. Fraud
13 prevention is elemental in a lot of different ways.
14 It's identifying the consumer in a card-not-present
15 transaction. It could be as simple, by the way, as a
16 retailer who doesn't have a bricks-and-mortar operation
17 trying to understand whether or not an address to which
18 they're sending a very expensive item is or is not
19 zoned residentially.

20 It could be devices today, and device
21 recognition strategies, to try to understand whether or
22 not I, with the -- if I'm a business and I have a
23 current, ongoing relationship with a consumer, whether
24 or not I recognize the device that the consumer is
25 using as he or she engages in these transactions.

1 So there's layers and layers of fraud
2 prevention that occur. It's all seamless. We don't
3 see it, we don't feel it, we don't think about it.
4 We're only upset when we discover that we've become a
5 victim of some type of crime.

6 Nine billion times year a our members' data is
7 used in what we'll call a risk transaction of some sort
8 in the United States. Our members are also the largest
9 global companies, delivering and propagating these same
10 types of services around the world, to some of the
11 fastest developing economies, economies like Brazil and
12 India and so on. They know what they're doing.

13 They are managers of big data. They are
14 managers of big databases of data. It's primarily
15 structured information, though. Sometimes it's hard to
16 know what the definition of big data really is, but the
17 kind of data that our members are gathering could be
18 derived from fairly sort of pedestrian sources. It
19 could be public record data gathered in the United
20 States that could be used, which helps us with mortgage
21 frauds and flipping and issues that have to do with the
22 safety and soundness of the mortgage that's applied to
23 a property.

24 And like I said before, it could be a
25 database of known fraudulent applications that have

1 been pooled by various retailers or other transactors
2 in the marketplace.

3 If there's a dividing line between Rachel and
4 me, though, and it's a great symbiotic dividing line,
5 there's a baton pass. Our members benefit tremendously
6 from the fact that there is this robust, incredible,
7 targeted system that connects consumers with what they
8 want. And in America, that's okay. We like buying
9 things. We like engaging in the marketplace. We like
10 seeing that offer that makes sense to us.

11 Then, there's a baton pass. A consumer
12 chooses to click and a consumer chooses to apply for
13 something. And that's more often where our members
14 then kick-in to the process. More often where -- and
15 in fact, if you're in the financial services space,
16 more often where you are complying with laws like
17 Section 326 of the U.S. Patriot Act, know your
18 customer. Red flags rules, promulgated by government
19 agencies such as the Federal Trade Commission, are properly
20 protecting consumers against identity theft.

21 So there's this, again, this confluence of
22 dataflows that occur on the front end of an
23 application, which is occurring sometime after I've
24 seen banner ads or I've shopped in bricks-and-mortar
25 stores or done whatever I do as a consumer to figure

1 out what it is I want and at what price I want it and
2 so on and so forth.

3 But some of those laws that regulate our
4 industry, Fair Credit Reporting Act, Driver's Privacy
5 Protection Act, the Gramm-Leach-Bliley Act, Title 5,
6 again, not the topic of today, but important for you to
7 know that these laws wrap around a lot of these
8 different databases that are out there for consumers.
9 Because these databases particularly -- and Rachel used
10 an important term, eligibility. Once you cross over
11 the line into eligibility, one you cross over into what
12 I call gate-keeping, you get a yes or no. Or the yes
13 that you get is the best yes on the list or it's a
14 qualified yes, somewhere down on the list, you pay us a
15 little higher price or a lower price, all of that is
16 regulated under a variety of, for example, fair lending
17 laws, the Equal Credit Opportunity Act, the Truth in
18 Lending Act, and so on and so forth. So once you get
19 into the application context, you're back in that world
20 of laws that wrap around the transaction.

21 So let me just give you a couple of examples.
22 Lending Club, I want to go back to Lending Club. I
23 don't know a lot about Lending Club, but I'm just
24 saying that if Lending Club has a new, innovative way
25 of managing big data to try to make a lending decision,

1 even though Lending Club is using new data sets, they
2 are still obligated to comply with the Equal Credit
3 Opportunity Act. They are still obligated to comply
4 with the Truth in Lending Act. They are still
5 obligated to make sure that they don't have disparate
6 impact problems. The confluence of all of these laws
7 still applies. So there's nothing new about the use of
8 that type of information, when it's in the context of
9 that type of application process.

10 And then the different example. The CFPB was
11 looking an annualcreditreport.com, by the way. By the
12 way, let me say that again, get your free report every
13 year at annualcreditreport.com. It's my little
14 advertisement, but not a bad one, right? Not a bad
15 one.

16 So 16 million consumers roughly are looking
17 at free credit reports each year, out of 200 hundred
18 million-plus consumers, so it's not a huge amount. So
19 the kinds of analytics that have been discussed by
20 Claudia, and also by Rachel, might be one way for us to
21 reach out into that community of consumers more
22 effectively and try to find those consumers who we
23 think would benefit from accessing free credit reports,
24 but aren't doing it today.

25 So there's, I guess, a social good example of

1 how there's a nexus between get your free report, be
2 credit report literate, make sure that you understand
3 what's in your credit report, you know, all of those
4 things that we believe in, and the analytical tools
5 that can allow us to kind of get to that point and
6 reach those consumers who we think are most likely to,
7 you know, point-and-click and move forward.

8 So that's just an example of the power of
9 this kind of information and how it connects consumers
10 with, sometimes, maybe something they don't know that
11 they should do, but they get it.

12 MS. ARMSTRONG: And that's a great example,
13 Stuart.

14 As Andi and I are mindful of the clock, we'd
15 like to turn quickly to Ed and Pam to see if they could
16 mention some other products, what they might be used
17 for, and then before Ashkan's presentation, we want to
18 talk about data accuracy.

19 So I want to make sure we get to that before
20 the top of the hour.

21 MR. MIERZWINSKI: Well thank you, Katherine
22 and Andi. My work at U.S. PIRG is as a consumer
23 advocate. And I'm concerned not about the data, per
24 se, I don't think anybody is. I'm concerned about its
25 use and its impact on financial opportunity.

1 And I'm also going to give a disclaimer, as
2 Stuart did, that I'm not here to talk about the Fair
3 Credit Reporting Act, but I have to mention it
4 peripherally, or at least in passing.

5 For 40 years, financial marketing of the most
6 import kind, based on your credit report, the most
7 detailed profile about you, has been governed by the
8 prescreening rules of that Fair Credit Reporting Act.
9 That law says, if a company wants to use your detailed
10 financial profile to market to you, it can only market
11 to you for credit or insurance purposes, not direct
12 marketing, it must give you a firm offer of credit, and
13 you have the right to say no to that use of your
14 information. You have the right to say no to using
15 your financial profile for marketing to you. And the
16 kind of marketing that can be done is extremely
17 limited.

18 I am very concerned that we are moving to a
19 new system of unregulated, wild west companies, running
20 roughshod over consumer rights on the internet and
21 making decisions about what ads to serve to you, maybe
22 not directly determining eligibility yet, but deciding
23 what box to put you in, what place to direct you from
24 your cookies and from the other information that they
25 have about you, and possibly causing you to pay more or

1 get fewer opportunities than other consumers. That's
2 the short version, I've got much more to say.

3 And by the way, it's USPIRG, P-I-R-G. If you
4 go to my blog, on the homepage today there's a lot more
5 detail and links to some of our materials, including my
6 paper with Jeff Chester at the Suffolk University Law
7 Review.

8 MS. DIXON: Good morning. Thank you so much
9 for the invitation, I really appreciate it. This is a
10 great panel and I really appreciate the opportunity to
11 share a discussion about this important topic.

12 So let's begin with the fact patterns here.
13 So the first fact pattern is that scores are
14 proliferating. In the past, when the credit score was
15 developed, the credit score used limited factors, well
16 under 100, they were controlled factors. In fact,
17 those factors that are used in the credit report are
18 regulated. They cannot be discriminatory, they cannot
19 be prejudicial. And Congress did this for a very good
20 reason, the same kinds of reasons that they passed the
21 Civil Rights Act. There should not be any kind of
22 hidden discriminatory factors in scores, this we can
23 all accept as a baseline. So that's one thing.

24 The second thing is that the large data set
25 world that we're living in is not going to reverse

1 itself somehow. That genie is well out of the bottle.
2 So given that, really one of the ways that all of us
3 make sense of our world is by shortcutting.
4 Understanding data and predictive analytics allows us
5 to do that, the machines do the hard work of sifting
6 through petabytes of data for us. So the results of
7 that are spit out are often scores. Scores can have
8 varying ranges, they can have varying values, and can
9 mean completely different things, depending on the
10 factors that are fed into the score, as Claudia
11 discussed, the algorithm, and then, of course, we're
12 talking about the use of the score.

13 The really important thing here is that the
14 credit score had a very focused purpose. Today, with
15 the real proliferation of the technologies that allow
16 more and more retail and enterprise and small
17 businesses to create predictive analytic scores and
18 tools and results, it's becoming more important to find
19 out what other scores are out there. And that's the
20 second fact pattern, there's a lot. So that's the
21 second thing.

22 The third thing is this, the credit score, as
23 a controlled score, has been very, very carefully
24 observed and has a lot of oversight. The new scores
25 don't enjoy that same kind of protection. So here's my

1 thinking on this. We really need to understand that
2 there is a continuum of scores here. Not all scores
3 are bad. In fact, some scores are actually helpful.
4 The Equal Credit Opportunity Act mentions specifically
5 credit scores and how they can assist in reducing
6 discrimination in lending. This is a good use of a
7 score and it's a regulated use of a score and it's
8 appropriate.

9 So today, we really need something like that
10 to look at these scores that have proliferated and are
11 new, so let's talk about some specifics. The credit
12 score, a few factors, and a static score, doesn't
13 change that often and that much, unless you really game
14 the system. And that's a whole different matter. Not
15 for this panel, right?

16 If you take an aggregate credit score,
17 however, an aggregate credit score and actually some
18 modeled credit scores, can use 1500 factors. These
19 factors are in a big black box, we don't know what
20 those factors are, we're not told what the factors are,
21 and yet Claudia's presentation was completely correct
22 when she said, look, you have the factors that go into
23 a score, really that's everything. Good factors in,
24 nondiscriminatory factors in, much better chances of
25 getting a nondiscriminatory score on the backend.

1 But if there are credit-related or any kind
2 of eligibility-related scores that have discriminatory
3 or prohibitive factors that are used in the score soup,
4 we've got a big problem. But we won't know that we
5 have a problem, because right now most scores are
6 secret, with the exception of what I would call social
7 scores like Klout. Consumers don't have the
8 opportunity of learning about the scores, because there
9 is no transparency for them and certainly the factors
10 are secret. So we've got big problem there.

11 Now having said that, there's something
12 really important to understand. And I'd like to echo
13 Ed's remarks. We did a thought experiment and we asked
14 ourselves, could the Klout score, a social-influenced
15 score, be covered by the Fair Credit Reporting Act.
16 And you just can't get there. There's a real first
17 amendment issue here that we have to grapple with.
18 There is such a thing as free speech. And you know, if
19 someone is quoted in the Washington Post, and the quote
20 happens to be not so great, right, and it makes the
21 person look bad and they don't get a job because of
22 that quote, does that mean the Washington Post should
23 be regulated? No. None of us think that, right?

24 So we have to be really careful here. It's
25 attention.

1 MS. ARMSTRONG: Pam, that's an excellent
2 point. And I want to save some of this conversation
3 about the parameters until the second half.

4 And although I have a very specific thing I
5 want Joe to share with us, I think that right now, this
6 is an excellent segue into the accuracy issue. And as
7 Claudia mentioned, quality is hard. And as we look at
8 it, accuracy has two components. One is going to be
9 the model and the other is going to be the data.

10 So I'm wondering if anybody could speak to
11 how companies determine whether the data -- well,
12 whether there are certain sets of data that are
13 inherently more accurate than others and is data
14 accuracy relevant for all types of scores? So I'd like
15 to throw that out for a few minutes, if anyone wants to
16 comment on that.

17 MS. DIXON: Can I just jump in?

18 MS. ARMSTRONG: Sure, please. Absolutely.

19 MS. DIXON: Data -- scores are coming from
20 public data, they are coming from demographic data,
21 enterprise, social, even some health data. There is
22 even financial interest and activity. So the accuracy
23 of data is a huge issue. It's very, very difficult to
24 create a score above 95 percent, everyone knows that.
25 I think that, from the analysts I've talked to, a score

1 above 85 percent is just awesome.

2 But I think that there's really no way for
3 anyone who uses thousands of factors in a score to
4 completely assure that each factor is accurate. I just
5 don't see it.

6 Now hopefully, there will be a lot more
7 transparency in the industry and we can find out a lot
8 more about this. And that's what's incredibly
9 important.

10 MS. THOMAS: Can I add to that?

11 MS. ARMSTRONG: Sure, absolutely.

12 MS. THOMAS: So I think when we think about
13 accuracy first, again, from the marketing perspective,
14 you want to have an accurate ability to predict what
15 someone is going to be interested in. You are more
16 likely to have a sale at the end of that, so yes, the
17 data being accurate in order to make that prediction
18 out of predicted analytics is a good thing.

19 That said, when it comes to consumer
20 protection, I think it's incredibly important to look
21 at the relationship between the importance of accuracy
22 and the use of that data. Data is data is data.

23 So when we're talking about marketing, if
24 data is incorrect, you're going to get an offer that
25 isn't relevant to you and that's the end of it. If

1 your credit score is inaccurate, you could be denied
2 housing, insurance, et cetera, et cetera. Very
3 important permissible uses under FCRA.

4 So I think it's important to play this out to
5 the end. When we're talking about data, what is it
6 being used for and, at the end of the day, that
7 determines the importance of its being accurate, linked
8 to the potential impact on a consumer, in terms of harm
9 to their way of life.

10 MS. ARMSTRONG: Ed. Oh, I'm sorry. Ed and
11 then Joe.

12 MR. MIERZWINSKI: I'll just be very brief.
13 But I'll say this, how do you determine accuracy?
14 Well, we need, as Pam said, more transparency. And
15 there have been a number of studies by consumer groups
16 where they have requested information about their
17 profiles from various data brokers and others. And the
18 profiles, when they've been provided, have been
19 incomplete and inaccurate.

20 By the way, I'll just make one quick point.
21 I've been a member of REI for 40 years, I've shopped
22 there for 40 years, I've been a member -- not a member,
23 but I've shopped at L.L. Bean for 40 years. And for some
24 reason, L.L. Bean, for the first time ever, just sent
25 this non-fisherman the fisherman's catalog. Maybe

1 they're trying to expand my horizons? I don't know.

2 But I thought that was pretty interesting.

3 MR. TUROW: I also wanted to add about the
4 question of accuracy. In huge models, from what
5 Claudia was saying and other things that I seem to
6 know, it is very difficult to know what about the model
7 is accurate or not accurate when you're predicting
8 something.

9 And the other thing I wanted to say,
10 connected to this, is HIPAA and Gramm-Leach-Bliley
11 aside, there are lots of places to get data like that,
12 that you can go around these laws.

13 There is, for example, a company called Medix
14 which has a website that will give you discount coupons
15 on serious health problem medications. So you go to
16 that website and you write in what your problems are
17 and then you get these discounts. And you don't know
18 what they're going to do with those data. Privacy
19 policies are fascinating obfuscatory. And it is very
20 difficult to know.

21 I think we have to expand the notion of --
22 the notion of a credit score and a data broker. Is
23 Kroger a data broker? Now, reading Kroger's privacy
24 policy, they seem to imply that they don't sell their
25 data, okay? But is it not selling data if Kroger

1 allows advertisers to put ads on sites which track
2 people and then, through the cookies, essentially they
3 are buying data that way from Krogers? It's a
4 side-door data broker activity, I would argue.

5 And so we have to think a little more
6 broadly, I would argue, about data brokers and about
7 the ways in which companies try to get around some of
8 the obvious laws about protection.

9 MS. ARMSTRONG: Just one second. I wanted --
10 before, Claudia, you talk about the accuracy thing,
11 before we leave the products and their uses. Joe, if
12 you could describe the KLM example that you shared with
13 Andi and I when we spoke with you.

14 MR. TUROW: Yeah, I remember reading about
15 this. It's not so much a big data issue, it's just
16 simply the notion that people can find out, through the
17 website, if you're going alone on a KLM flight, what
18 kinds of interests other people have and then you can
19 decide whether or not you want to sit next to that
20 person. It's not clear to me that other people have --
21 presumably everybody has the right to say they want
22 their interests put out there. If they didn't, that
23 would be a fascinating question of predictive
24 analytics.

25 But let me, as long as we're getting at this,

1 say one thing that did happen to me that I think people
2 would not have predicted. I was on a United Airlines
3 flight coming from Wisconsin into O'Hare and the flight
4 to Philadelphia was canceled. They told me to go to a
5 customer service place and scan the boarding pass I had
6 for the canceled flight. When I did that, it gave me a
7 number. And to the right, there was a monitor that
8 said, the amount of time that you will be taken to be
9 served will relate to your status, your loyalty status,
10 with the airlines.

11 Now I don't think that most people -- and I
12 was very fortunate, I had a lot of miles. But there
13 were these poor people sitting in the back, they
14 weren't treated for a long time. And the implication
15 of it is, some people will get flights and other people
16 won't. So --

17 MS. ARMSTRONG: So we now have a marketing
18 risk/credit and airlines?

19 MR. TUROW: Yeah. I guess I'm saying is, we
20 don't know, when we give these data, what the
21 implications are.

22 MS. DIXON: Can I jump in for just a second?

23 MS. ARMSTRONG: Please. Everybody can jump
24 in quickly, and then we're going to move to Ashkan.

25 MS. DIXON: I'm most -- I'm not as concerned

1 about ads as I am about eligibility issues. Our focus
2 and our research in this area has been on eligibility
3 uses of marketing and noncredit data outside of the
4 FCRA and outside of HIPAA.

5 I understand that the ad information is very
6 fascinating. It's fascinating to me, too, on a
7 research level, but we're very concerned about the more
8 impactful scores. And those are definitely use of
9 health data as factors, use of scores in health, which
10 is being done today, by the way, that include non-HIPAA
11 information held outside of the medical establishment
12 and also use of discriminatory factors in eligibility
13 decisions, which is happening today.

14 MS. PERLICH: I wanted to quickly jump on the
15 accuracy. I'll keep it -- the first one, there is an
16 inherent tension between the ability to regulate and
17 keep the model understandable, or the score, and the
18 accuracy it can reach. My being able to add 100 or
19 1000 more factors into the model, I can double the
20 accuracy and you will not understand it anymore. There
21 is that tension, we have to be aware of it. It's
22 simply the ability to predict is a function of the kind
23 of variety of stuff you give it to start with.

24 My second comment is on data brokers and
25 scores. One of the reasons we have the data, we use

1 the data we use, which is what I call primary, I
2 observe people's actions, is anything derived from it
3 that I can buy from data brokers is absolutely awful,
4 in terms of accuracy, from what I can tell. So all the
5 scores, whether it's done demographic, that I can buy
6 your gender, and typically people are both -- so my
7 experience has been that the data that somebody else
8 has derived somehow is really problematic. And at that
9 point, it becomes completely useless.

10 MR. PRATT: So just a couple of quick -- I'll
11 move through these like a list.

12 MS. ARMSTRONG: That's fine.

13 MR. PRATT: So just a quick thought about
14 data brokers overall, and this is just because, at
15 CDIA, we deal with that term quite a bit these days.
16 It's a newish term and it's a really undefined term.
17 So I just want to make clear that really, when you're
18 thinking about data and analytics, and actually, Joe, I
19 think you said it well, it could be a closed system of
20 data that has been aggregated by a single entity, like
21 Kroger, or a search engine, for example. And they may
22 not be selling the data, but they're certainly inviting
23 people in to make use of that data, to deliver the
24 advertisement. So we don't see, you know, this sort of
25 third party versus first party thing as particularly

1 relevant to the data broker issue overall, but I just
2 think it's important to lay that out and say, you know,
3 that there's both.

4 With regard to credit versus noncredit, and
5 this goes to Joe's point about getting around laws,
6 nobody is getting around laws. And we may have a
7 debate about transactions of the definitions of those
8 transactions, and I think that's what Ed is kind of
9 driving at, but nobody's getting around laws. If
10 you're engaged in making a lending decision, you're
11 regulated by the laws which regulate lenders. And if
12 you're doing it outside of those laws, you are
13 violating laws and Maneesha's team and others will go
14 out and find you and investigate you and prosecute you
15 for not complying with the financial services laws that
16 apply today.

17 With regard to developing credit scores, I
18 don't like the term credit scores versus this better
19 term, analytics. Because credit scores makes everybody
20 think about the credit score that may be based on a
21 credit report, but that's not really the point. And by
22 the way, I think a credit score developer would say, it
23 doesn't matter how many factors I have, I must build a
24 score that is successful in the marketplace. It must
25 be saleable to somebody who sees the outcome, sees what

1 happens.

2 So if I'm developing it for marketing, I want
3 to see that people click on the ads and engage and make
4 purchasing decisions, because it's a good analytical
5 tool that leads me to some place where I want to be to
6 make a yes decision, because I like the yes decision
7 I'm making as a consumer.

8 Credit is a little bit different. It's about
9 prudential lending, of course. And so regardless of
10 whether it's 100 or 1,000 different factors, it has to be
11 statistically sound, it has to be empirically derived,
12 and whether or not it's a first-party score that's
13 developed by the lender in house, based on big data,
14 sort of the old Zest Cash model, or whether it's a
15 score that has been developed by any one of CDIA's
16 members, who are some of the biggest data analytics
17 companies in the country, whether it's a fraud score or
18 whether it's a score for credit, the outcome is the
19 key. It isn't measuring factor-by-factor precision.

20 But yeah, developers will look at a whole
21 variety of factors. They may look at 100 times the
22 number of factors that ever end up in the score,
23 because they're trying to find the right sauce of
24 scores that will lead to an excellent lending decision,
25 allowing them to penetrate and get to more yeses than

1 nos, but to do it in a prudential, safe and sound,
2 sort of banking safety and soundness way.

3 MS. ARIAS: So Stuart --

4 MR. PRATT: So that was just some quick
5 thoughts in all of that.

6 MS. ARIAS: I think you raise an excellent
7 point. And it's actually a follow-up to you, Pam,
8 because I think you brought this up and he's
9 responding, right? What is an eligibility use that
10 falls outside of the FCRA? What is it that you are
11 envisioning in your comments?

12 MS. DIXON: Okay. So look, there are scores
13 today that are called either aggregate credit scores or
14 modeled credit scores, so let's talk about aggregate
15 for a second. The Fair Credit Reporting Act, our
16 lovely, trusty Fair Credit Reporting Act, applies to
17 individual consumers. Aggregate credit scores apply to
18 a neighborhood.

19 So if a person lives in a neighborhood, it's
20 kind of like in old England where if you lived in a
21 house where there was a debt collection, then you were
22 also a bad apple, it's kind of the same idea. And I'm
23 sorry, but how -- if you are using an aggregate credit
24 score that is a very close proxy for a credit score,
25 and offering a financial product or an insurance

1 instrument to a consumer, I think technically they're
2 not covered, right?

3 However, it's a really important eligibility
4 decision or a product offering and this is where I
5 think we have enormous tension. And these, I think,
6 are the important scores to focus on and they are
7 secret scores. I can't purchase my aggregate credit
8 score, I can't. It's not regulated.

9 MS. ARIAS: So I know people want to respond.
10 And I think the conversation is starting to move to the
11 idea of what the effects of these scores are, right?
12 So before we jump to effects, we really wanted to get
13 Ashkan to give us his presentation, if he wants to come
14 up.

15 So Ashkan is going to give us a brief
16 presentation about some of the privacy issues
17 associated with scoring products, especially about some
18 of the research that he and other researchers have done
19 on emerging trends in online pricing with the use of
20 these scores.

21 MR. SOLTANI: Can I just briefly --

22 MS. ARIAS: Yep.

23 MR. SOLTANI: -- just make a comment on
24 accuracy?

25 MS. ARIAS: Absolutely.

1 MR. SOLTANI: One thing I want -- and I'll
2 talk about this a bit in my presentation, but I want to
3 clarify that, with regards to accuracy and these
4 traditional models, this stuff isn't as black and white
5 as we are used to. It's not whether you're qualifying
6 for -- well, some of it is, whether you are qualifying
7 for a job or whether you are qualifying for credit.

8 But we should also be mindful of the ways
9 these aggregate scores or these numbers are used to,
10 what I want to call do fuzzy nudges, right? These are
11 things like how long you wait line, is one of those
12 things, where the score might have an effect on kind of
13 subtle behaviors that kind of get up close to some of
14 the things we care about. Other things are like how
15 long you might wait at a call center. So call centers
16 are actually profiling for customer service.

17 And I'll talk about this but, for example,
18 what credit cards you are shown, what credit card
19 objects you are shown and what you have an opportunity
20 to apply to. You know, how far down on the page or
21 whether it's on the next page, I think those things
22 also influence. They're not direct kind of credit
23 scoring type products, but they kind of influence -- we
24 know most people don't go to the second page, right?
25 We know most people will kind of see the options

1 represented. And sure, you can definitely dig, but it
2 essentially nudges people to a particular outcome that
3 I think we start, you know, caring about.

4 And they might use explicit factors. They
5 might not be -- they might be just data driven, right?
6 So, Google, for example, is notoriously well-known for
7 their HR recruitment algorithm. So when you submit a
8 resume to Google, they have this awesome matching
9 system that will kind of present you for potential
10 jobs. And it's not clear whether -- and it's likely
11 that they're using, say, sexual -- you know, sex or race
12 as an indicator, but there might be that latent
13 property that's in the system, that might emerge, that
14 we care about. But it's essentially one of these fuzzy
15 messages which is, ten resumes are presented to the
16 recruiter and they are based on a bunch of factors that
17 are essentially scoring, but not in a direct yes or no
18 way, but just the probability of. And those things are
19 a bit fuzzier, so I'll talk about a bit of those.

20 MS. ARIAS: Fabulous. Did you -- yeah.

21 MS. ARMSTRONG: So as Ashkan is setting up, I
22 think I wanted to just observe that Pam and Ed have
23 noted that we do have a statutory framework in the FCRA
24 that covers some kinds of data.

25 And I think they're correct to point out that

1 we're talking about these non-FCRA products, but using
2 some of the lingo that the FCRA uses, and that's a bit
3 of a challenge.

4 But now, Ashkan?

5

6

7

8

9

10

11

12

13

14

15

16

17

18

19

20

21

22

23

24

25

1 EMERGING TRENDS IN ONLINE PRICING

2 MR. SOLTANI: Sweet. All right. Oh, that's
3 loud.

4 Everyone, so I want to just briefly talk
5 about some of the research. So I want to just keep it,
6 since it's a five-minute quick presentation, I'm just
7 going to talk about some of the research that I did in
8 the past on kind of scoring and use of data.

9 And so I'm going to briefly talk about the
10 methodology and how I did it, the findings, and some of
11 the -- some comments on data sources. And so most of
12 this research was from a piece we did for the Wall
13 Street Journal on sites varying prices and offers to
14 consumers based on data about them.

15 And the methodology was really kind of basic.
16 We kind of crawled the web with a variety of
17 user-agents. This is, you know, your mobile device or
18 your browser, it's known as user-agent. Sometimes
19 Firefox is a user-agent, sometimes Safari means you're
20 using an Apple product, usually. You know, whether you
21 are using a mobile device, that's your user-agent.

22 We looked at different proxies for different
23 locations in the world, like multiple locations in the
24 U.S. and multiple locations in the world, and then we
25 built profiles. We built essentially user profiles

1 that would, say, browse, you know, (inaudible) sites
2 and Scrabble kind of games versus, you know,
3 potentially someone that only connects to the West
4 Coast that checks car sites and electronics, right, to
5 try to generate profiles. And we verified these
6 profiles by looking at various dashboards for the
7 profile managers.

8 And so we would essentially go through and
9 iterate the web and check a particular website, say,
10 1,000 times or, you know, tens of thousands of times
11 with the right permutations to see, statistically, what
12 offers get offered, you know, presented to who. And so
13 essentially kind of black-boxing or attempting to
14 black-box some of these.

15 And so some of the basic findings. So
16 user-agent, this is, you know, what browsers people
17 use. Some people might have kind of read this article
18 where, this wasn't our research, but it was another
19 team, but they had identified how Orbitz was simply
20 showing luxury hotels to Mac users, right?

21 So this was, how far down on the page or
22 whether you have to go to the next page. And this is a
23 subtle nudge. They argued that, well, look, like Mac
24 users are posh, they want to spend a lot of money on
25 hotels, so let's give it to them. There's no problem

1 with that, this is just kind of a highlight. We
2 actually found that, in fact, Orbitz was giving
3 discounts, they'd call these Mobile Steals, to mobile
4 device users, smartphone users, right?

5 So again, probably no problem with that.
6 This was actually not Orbitz doing it, this was the
7 hotels providing these offers through Orbitz. Orbitz
8 provided them the functionality, the technology to do
9 it.

10 But one thing to think about is, for example,
11 who buys smartphones? Usually people who buy
12 smartphones have some disposable income to pay for the
13 data plan and pay for the \$200 for the phone
14 versus the free device. This was a few years ago. And
15 so again, a good proxy for a loss leader for higher net
16 worth individuals possibly, but also simply just using
17 the user-agent as a proxy for this kind of thing.

18 I don't know if people fly, but in-flight --
19 probably one of my first experiences was when you fly,
20 like on Virgin America, and you have in-flight wi-fi,
21 the price they charge you is based on your user-agent.
22 So this is both my desktop, but one advertises as an
23 iPhone and the other advertises as a regular, you know,
24 Firefox browser and they charge different prices.

25 And they might argue that you -- you know,

1 maybe mobile phone users use less data than iPhone.
2 Although both have an iPad video streaming app, for
3 example, so it's not clear. But again, this is another
4 example of like charging different prices. I don't
5 know the legality of this, don't try this at home kind
6 of thing, but it's a proxy for your device.

7 So location is another -- and Pam kind of
8 raised a really good point about kind of location being
9 an indicator for other factors, not just where in the
10 world you are, right? So we looked at Staples, right?
11 So Staples is the office supply store and they were
12 charging different prices for goods based simply on
13 your zip code.

14 And kind of we dug into a bit and it turns
15 out that, in fact, the algorithm seem to have a higher
16 likelihood to charge you more based on whether or not
17 you were near, further or closer to a competitor's
18 store. So they mapped out where the competitors were
19 and essentially were charging you, you know -- in
20 staplers, it was a dollar or two, but on some of the
21 other items, it was up to \$100 for the same
22 safe. So you could order something online and,
23 depending on where they thought you were, they would
24 charge you a different price for the same good, right?

25 We also found that it wasn't just Staples.

1 Other suppliers, Home Depot, for example, Rosetta
2 Stone, were giving you discounts based on where they
3 thought you were, right? Where you were located. And
4 again, even Discover, the kind of -- the credit card,
5 was providing their it Card offers only to certain
6 regions.

7 So if you tested the website, if you visited
8 the website or if you visited sites that featured their
9 product, they would only show that it Card to certain
10 regions. The card had different benefits, different
11 kind of deals, essentially, associated with it.

12 And what's interesting is we also looked at,
13 for example, try to correlate the Staples stuff with
14 weighted average income and, in fact, there was a
15 correlation. So the places where people were getting
16 charged more were, in fact, places -- places that
17 people were being charged less were, in fact, places
18 where people made more.

19 And then we're -- and so again, this is an
20 interesting kind of commentary where it's good enough
21 to provide offers or show you deals, you can always go
22 to a store to see what the price is. But online, it
23 was a little bit different because, in fact, all you
24 have to do is, in this case, you didn't need a proxy,
25 you could just set your cookie to whatever zip code you

1 want to pretend to be, and they were relying on this
2 inaccurate signal as a way to price you.

3 And then the last kind of important component
4 of that methodology was kind of permutations and
5 profiles. And I'll admit this was kind of one of the
6 least kind of successful parts of our research,
7 partially because it is very difficult to black box the
8 profiles, as they change each time you sample them, you
9 corrupt your profile each time you use it, right? So
10 if I check a kids site as an adult, I might then
11 attribute to those factors.

12 The other thing is the spam algorithms and
13 the fraud detection algorithms are incredibly good, so
14 they quickly identify whether you are a human or not
15 and so they kind of -- the ad engines will kind of look
16 for click fraud and so we were tripping up a bit
17 against that. I have a new methodology of how I would
18 do this next time, which is a bit more robust, kind of
19 crowd-sourcing it essentially, or maybe more of like a
20 botnet. But a consensual botnet. A consensual botnet.

21 But some of the things we found, for example,
22 Nextag is a search engine where you can search for
23 products, right? You can search for, again, I don't
24 know why we were focusing on scanners and office
25 supplies, but if you went through Nextag, you would get

1 cookied as a Nextag kind of customer. And as such, you
2 would get different offers, you know, up to \$50 to \$100
3 difference for the same items based on whether
4 you had these cookies.

5 So again, profile-based kind of -- and they
6 were doing really clever stuff to not trip up, not to
7 let their competitors know that they were charging
8 lower prices. So they would, in fact, show the price
9 as a GIF, as an image, so that if you crawled their
10 site, the price would be \$499, a computer would think
11 the price was \$499, but the image that a human would see
12 would be \$350, right? And so they were trying to
13 actually adjust and score differently on this site and
14 then let users see the price. It was kind of some
15 clever stuff they were doing.

16 And then finally, this is earlier work
17 that one of my colleagues did and then we followed-up
18 and verified the same results, which is CapitalOne
19 credit cards. When you go to their site and try to
20 pull up -- I think Emily actually worked on this story
21 as well. When you kind of pull up a website and
22 different credit card offers, you would get --
23 essentially CapitalOne would ping a data supplier,
24 X+1, which is one of these kind of data networks, and
25 they would score you as the type of customer you are,

1 the type of credit you are likely to have. And those
2 would, in effect, show what credit card offers you
3 received.

4 And ultimately, of course, when you went
5 through and applied for the card, the credit decision
6 would hit a real credit check, right? Your
7 qualifications of whether you qualify for one would be
8 coming from, you know, Experian or one of these
9 databases. But the offers you were given were based on
10 this kind of fuzzy data that we're talking about.

11 And we found, you know, we found the same
12 type of thing pulling data from Double-Click and
13 RU4, which is X+1. This is still -- this was last
14 night, or a couple of nights ago, I just verified that
15 they still use these indicators. And to the degree
16 that, you know, Claudia said, we all know what data --
17 some of these are actually explicit. So some of these
18 they will explicitly ask for the types of sites or
19 credit scorings and there is an API that specifies and
20 a programming interface that specifies the type of
21 customer that is.

22 So I've done some work with like some online
23 dating apps and they specify what your marital status
24 is or whether you smoke or whether you do drugs. And
25 these are not fuzzy factors, these are explicit

1 categorizations of what the data broker thinks. And
2 they could be inaccurate, but they are at least
3 specified explicitly, which is what's interesting. So
4 whether you are high credit or medium credit.

5 And mostly, I want to just talk about the
6 data sources, because this stuff is made possible
7 by a number of front-end engines. This is Omnitures
8 Test and Target Suite, all it is is it lets you kind of
9 experiment with different offers, different profiles,
10 and see what's the most optimum for whatever task
11 you're trying to achieve.

12 And so again, nothing inherently wrong about
13 the system. It's a very easy-to-use, quick-to-use
14 system. You can vary the language and you can vary
15 some of the attributes of, you know, the price, et
16 cetera, but the key is that you can integrate this with
17 a variety of data sources, right? So you can pull
18 data, you can use for A/B this testing, a variety of
19 factors.

20 This is, for example, geo-targeting or sex or
21 age. And the question -- the thing that it raises is
22 that you have these sophisticated tools that simply are
23 just doing optimization, right? But they are pulling
24 from a set of data, a large data set. Everyone has
25 seen this graphic, it's like the most overused graphic,

1 but it does indicate that almost everyone in this kind
2 of red box is someone to purport to sell some sort of
3 data or provide some sort of scoring that you can use
4 to use this kind of A/B testing.

5 And so this stuff is going to have
6 interesting outcomes that we've not anticipated,
7 relying on inaccurate data without a lot of
8 transparency, and very hard to black-box, as I've said.
9 And so I think that's kind of the topic we want to dive
10 into.

11 And just as a final note, we ordered the
12 same -- we ordered the same stapler for two different
13 prices and they both were the same. They worked the
14 same.

15

16

17

18

19

20

21

22

23

24

25

1 PANEL DISCUSSION

2 MS. ARIAS: Thank you so much. All right,
3 with that presentation, I really wanted to give the
4 chance for the panelists, particularly Rachel and
5 Stuart, I would like to give you a chance to kind of
6 give us your thoughts about some of the kind of
7 findings that Ashkan has found, in terms of the use of
8 these predictive models and the effects that it might
9 be having on consumers.

10 MR. PRATT: Do you want me to dive in or --

11 MS. THOMAS: Do you want to go first this
12 time?

13 MR. PRATT: Okay. So I'm just going to
14 quickly work my way through bullets and then Rachel can
15 do an excellent job representing a much more detailed
16 and probably better presentation of all of the details.

17 So a couple of things. First of all, I used
18 to run retail stores all across the Washington area in
19 another life, many, many years ago, and of course we
20 rewarded loyalty. I mean, I don't know what the
21 epiphany here is with -- you know, when I was on an
22 airplane and they were pulling bags off of the
23 airplane, you're darn right I wanted my gold card stuck
24 to my bag, because I was loyal to that airline, to be
25 the last bag they pull off the airline, because I'm

1 hoping my loyalty means something.

2 So I don't know that that's an epiphany, that's
3 been around forever. Everybody wants to sell, everybody
4 wants loyalty, everybody wants to reward loyalty because you
5 want more people to come back. So that's just kind of a
6 macro thing. There's no ah-ha moment there. Everybody
7 wants
8 to be treated as a loyal buyer, that's all. I mean, again,
9 whatever the point is.

10 With regard to differential pricing or
11 whatever the term is, just a quick reaction to that as
12 well. I mean, I go to the airline website and then I
13 go to Kayak or some other aggregator and I look across
14 both of them to see. So I guess the big message there
15 is, you know, frustrate the analytics companies and go
16 shop really aggressively and make sure that you
17 understand the different pricing opportunities that are
18 out there. And don't be linear in terms of how you
19 behave online. So again, I mean, I think there is a --
20 it's not that there's an unsafe marketplace out there,
21 but consumers certainly should shop.

22 With regard to the alternative data, other
23 data that's out there, just remember that these new
24 data sets are potentially going to allow us to reach
25 consumers who are often not included, consumers who are

1 sort of the unbanked and the under-banked, and to bring
2 them into traditional lending contexts and others. And
3 it may start with marketing offers before you ever get
4 to firm offers under laws like the Fair Credit
5 Reporting Act.

6 So big data is an opportunity for inclusion.
7 It's got to be done right, the accuracy standards will
8 apply when you move into the lending context. The
9 fairness protections of ECOA and other -- Equal Credit
10 Opportunity and other laws will apply. The protected
11 classes of consumers are protected. But that's a
12 really important point, that these data are
13 opportunities to include, not just to exclude. I mean,
14 I think so often this is a glass half-full kind of
15 discussion. I think it's a full glass discussion,
16 there's an enormous amount of opportunity here.

17 It's good to have a panel like this, I think,
18 to flesh out a variety of views. I think it's a really
19 helpful panel, I'm learning. It's good for me to be
20 here, so I appreciate Andi and Katherine having me
21 here. But I just think there's a better story. It
22 isn't just a press down on consumers, but I'm still
23 just sitting here as a manager of businesses which have
24 relationships with consumers saying, you bet, I had
25 sales people who definitely went to the people who

1 bought the most first. Because that's how I got my
2 profit per square foot and that's how I continue to pay
3 salaries and monthly salaries that I had to meet.
4 That's all there is to it.

5 MR. SOLTANI: Just a quick comment. I'm
6 curious, who wants to be included in that higher priced
7 consumer category?

8 MR. PRATT: That's why you shop.

9 MR. SOLTANI: Right, but I'm --

10 MR. PRATT: I mean, that's why you shop.
11 That's why my wife is a much better shopper than me,
12 she always has been. She berates me all the time
13 because I would go to a big-box retailer and buy
14 everything at one store. My wife shops at four
15 different grocery stores because of the quality of the
16 product and the prices of the product. We just are two
17 different behaviors. Those are two different behaviors
18 in the marketplace.

19 MR. SOLTANI: So the shopping behavior here
20 would be, you know, building an architecture like I did
21 to shop for a stapler, right?

22 To find different prices, you have to delete
23 any of this information associated to you. And God
24 forbid you use an authenticated source like Google or
25 Facebook, that requires a login or is tied to your

1 credit card, to your purchase device. So you have to
2 then use anonymous cash and all this kind of stuff. I
3 think that's a little much for most consumers.

4 MR. PRATT: Hmm.

5 MS. THOMAS: So I want to talk a little bit
6 about Ashkan's presentation, which I think was actually
7 incredibly -- not actually, it was incredibly helpful,
8 in terms of understanding how the backend works, right?
9 So thank you for that.

10 I think, you know, I agree with Stuart that
11 loyalty is something that consumers respond extremely
12 strongly to. They want to be, you know, in a loyalty
13 program. They want to be given that additional offer
14 because they shop in one place and not another on a
15 regular basis, et cetera. And those programs have
16 grown because that's what consumers have demanded, that
17 if I'm going to be loyal to you as a brand, then you
18 darn sure make -- make darn sure that I get something
19 back for it.

20 Now again, we can talk about the outer limits
21 of that when it goes beyond marketing, but as far as
22 marketing is concerned, loyalty makes sure that you get
23 better offers over time. But also let's remember,
24 businesses want new customers as well. So a business
25 is as likely to give a discount to a loyal customer,

1 it's equally likely to give a discount to a first-time
2 customer, to make sure that that customer gets involved
3 and then will come back and become loyal in the future.
4 So this isn't a matter of one or the other.

5 And just to sort of go back to the bottom
6 line here, Ash made a really great point about the
7 marketing offer. You might get one offer or the other,
8 but then there is that firewall to whether or not you
9 are actually going to be eligible.

10 And I think a helpful way to think about that
11 is, you know, the Fair Credit Reporting Act, I'm not
12 going to get into it, I promise, but it uses the term
13 consumer-initiated, in terms of the kind of
14 transactions that are covered by FCRA. The consumer
15 initiates it and then it's not in the consumer's
16 control what happens next, in terms of the eligibility
17 decision.

18 In marketing, it's a marketer-initiated
19 transaction, but it's the consumer who is in control of
20 whether or not they respond to that marketing offer or
21 they go around that marketing offer and say, that's not
22 really what I want, I don't want 20 percent, I want 50
23 percent and I'm going to walk in the store and say so.

24 MS. ARMSTRONG: And Rachel, I think that's a
25 really great point, but I think Pam and Ed are -- I

1 would like to hear what they have to say, because I
2 think they are talking a little bit about that very big
3 fuzzy space in between the loyalty marketing and when
4 you get into eligibility. So I'd like to --

5 MR. MIERZWINSKI: Well, sure. And you know,
6 I think what Ashkan was talking about is not -- he's
7 not against loyalty cards. He probably might have
8 some, he might have a rewards credit card, I don't
9 know.

10 But what he's against is consumers being
11 selected based on secret profiles to be chosen to pay
12 more. Nobody wants to pay more. Everybody wants to
13 pay less. But nobody wants to be put in a box where
14 they pay more. And in a nontransparent system, where
15 thousands of bits of our lives are being collected
16 about us, shared and used to decide who will pay more,
17 my concern is not with big data per se, my concern is
18 with, can we use big data in a positive way to promote
19 financial opportunity.

20 I don't want banks to figure out which
21 consumer we can ding for more overdraft fees. I want
22 banks to figure out how to serve the under-banked,
23 using big data to save money and encourage the use of
24 the right accounts that make sense for that consumer to
25 be able to build up assets.

1 Again, I have loyalty cards, I have rewards
2 cards. I think that some seats on an airline, some
3 seats at the last minute, seats right down in front at
4 Yankee Stadium, are worth more than others. But I
5 think a stapler is a stapler.

6 MS. DIXON: So this conversation has gotten
7 to really the good part, really. So I'm just going to
8 give the grab here. So look, big data is an
9 opportunity for inclusion and it's an opportunity to
10 help people. I've seen this with my own eyes, in other
11 countries and in this country. It's incredibly
12 important that we acknowledge that. And that when we
13 target vulnerable populations or use sensitive factors
14 that these are used with great transparency, oversight,
15 and consumer control and are unfailingly beneficial to
16 consumers.

17 So there should be no secret scores and there
18 should be no secret factors. As a result, and to
19 facilitate that, there's something that we can do, I
20 think, that is a fairly -- it's a tweak. And I'm all
21 for tweaks because they're doable, right?

22 So creators of consumer scores, whether they
23 be static or femoral, enterprise, public, et cetera, if
24 they stated the purpose of the score, if they stated
25 the composition of the score and the intended uses of

1 the score, and allowed uses of the score, then I think
2 that that would go a very, very long way in
3 transparency. And I believe that would also pull that
4 under Section 5 of the FTC Act and then we would have
5 some oversight.

6 We all know that Section 5 is broad and it
7 would be very difficult to enforce a lot of this;
8 however, it would provide a tweak and a first step
9 toward bringing fairness while allowing benefits to
10 occur. We have to have both, we have to have both. No
11 secret scores and no secret factors.

12 MS. ARIAS: I think Rachel wants to respond,
13 but I do want to followup on something that you just
14 mentioned.

15 You said there should be transparency and
16 consumers should know about it, but how do you
17 communicate this to consumers? Given that there are so
18 many scores and there are so many factors that go into
19 these scores, and also that, you know, they don't even
20 know they exist, right? So at what point do you
21 communicate this information to consumers?

22 MS. DIXON: I think there's no perfect or
23 beautiful answer to that. I think we're all struggling
24 with that right now. How do you communicate in either
25 a short or long or midterm or holographic privacy

1 policy? Those things are, I think, in the midst of
2 being decided right now.

3 But in the interim, a privacy policy would be
4 a great place. This has its flaws, I am the very first
5 person to admit this, but we need to start somewhere.
6 And I'm all for starting with a tweak. Because
7 protecting vulnerable consumers is a necessity, not an
8 option. And as a result, let's start somewhere.

9 MS. THOMAS: So I just wanted to add, I
10 couldn't agree more with Pam, the importance of making
11 sure that when vulnerable populations are at stake or
12 at target or the topic of conversation, transparency
13 and making sure that they are not treated in a
14 discriminatory way is incredibly important.

15 So I think the good news is that we do have,
16 not just FCRA but many laws that make sure that that
17 doesn't happen. There's FCRA, of course, the fair
18 lending laws, of course, apply there. And I would argue
19 that the Federal Trade Commission Act, the FTC Act,
20 Section 5, if unfair or deceptive acts or practices --
21 if the marketing or the advertising is unfair to a
22 vulnerable group in some way, that that would already
23 be covered.

24 DMA also thinks this is incredibly important,
25 such that we regulate that in our ethical code as well.

1 We have one of the first articles, in the almost 60
2 articles of requirements for any marketer doing
3 anything, is disparagement. Make sure that any
4 marketing that you undertake is not disparaging to any
5 population and particularly vulnerable populations.

6 So this is something where, if there are
7 problems, they are that we are not enforcing the laws
8 that we have and that we should be in greater, you
9 know, put greater resources toward that to make sure
10 that the kinds of things that Pam is talking about are
11 not possible. Protections exist, we have to make sure
12 that they are acted upon.

13 MS. DIXON: I don't think most of these
14 scores actually are protected, I really don't. I think
15 they --

16 MS. THOMAS: Can you give an example of --
17 like, just for the sake of --

18 MS. DIXON: Aggregate. Aggregate credit
19 scores, I think, are an excellent example and modeled
20 credit scores. So they are used to provide offers of
21 credit, and even to set initial insurance rates, right?
22 But --

23 MS. THOMAS: So an offer of credit though
24 could --

25 MS. DIXON: I'm not talking --

1 MR. PRATT: They're not used to set rates,
2 they're not used to set rates.

3 MS. DIXON: They're not used to set rates
4 for --

5 MS. THOMAS: -- would be covered by FCRA.

6 MR. PRATT: I just want to -- that's the
7 bright line, I think, you're dealing with, right?

8 MS. DIXON: That's correct, that's exactly
9 right.

10 MR. PRATT: Okay.

11 MS. THOMAS: Which is such an important
12 bright line.

13 MR. PRATT: Correct.

14 MS. DIXON: We're at the razor edge of where
15 the Fair Credit Reporting Act ends and something else
16 begins. And I'm talking about the millimeter to the
17 right where the something else begins. So I'm not
18 talking about a firm offer of credit, I'm talking about
19 the offers that really color and make a person's life
20 different.

21 And we haven't talked a lot about health
22 data. In the report we're coming out with next week,
23 we talk a lot about how health data is being used in
24 scoring. And this is health data that has been
25 acquired outside of HIPAA.

1 And when health data is put into scoring
2 factors, it is extremely prejudicial. And no one has
3 -- there's not a law that covers this. Well, a little
4 bit FCRA, but it's not applicable. So that's the piece that
5 we're concerned about.

6 MS. THOMAS: I hear what you're saying, but I
7 think, you know, I think the FTC has taken action in
8 these areas, and very important actions, to make sure
9 that FCRA is covering exactly where it needs to and
10 that there is no gray area.

11 I think the Spokeo case was a really good
12 example of that. You know, FCRA has worked for 40
13 years and I think that case showed that it continues to
14 work. If third-party data is used for a permissible
15 purpose under FCRA, then that data is a consumer report
16 and the agency or the organization is a consumer
17 reporting agency and FCRA covers it and the problem is
18 solved.

19 So let's make sure that that -- you know,
20 thank you. And let's make sure that those kinds of cases
21 continue to happen where, you know, FCRA-covered data is
22 being used in ways that are not in line with the law.

23 MS. ARIAS: I think Ashkan wants to jump in.

24 MR. SOLTANI: Yeah. So I'm --

25 MS. ARIAS: And Claudia.

1 MS. ARMSTRONG: And Joe.

2 MR. SOLTANI: So the backend verification
3 happens through the FCRA-approved process, but if I'm
4 never presented with the opportunity to apply for the
5 lower interest rate card, kind of where in the -- how
6 does that --

7 MS. THOMAS: There is no reason that you
8 should ever have to take a marketer or anybody else up
9 on the offer that you're given. That is completely
10 separate from --

11 MR. SOLTANI: But if I don't see --

12 MS. THOMAS: -- your eligibility to get the
13 product. So if you don't like the offer you have, that
14 isn't the only offer that is available to you.

15 MR. SOLTANI: Actually, so --

16 MS. THOMAS: That's the law.

17 MR. SOLTANI: When I tested the kind of
18 credit card sites, Chase for example, or CapitalOne,
19 when you would repeatedly visit the site, you would
20 never get, you know, one out of maybe 100 times, or
21 statistically a low probability of times, you would get
22 the other offers.

23 So as a consumer, if I reload the page, I'm
24 not given the choice to say give me the zero interest
25 card.

1 MS. THOMAS: Did you call the credit card
2 company to ask what offers --

3 MR. SOLTANI: Do most -- I mean, so this
4 rings to me a little bit --

5 MS. THOMAS: If I don't like the offer I'm
6 getting, I go somewhere else to try to find an offer
7 that I actually like.

8 MR. SOLTANI: Right, right. So let me kind
9 of --

10 MS. THOMAS: That's what I'm getting at.

11 MR. SOLTANI: Let me give an analogy that
12 might work. So everyone can vote, right? And you get
13 verified at your polling place.

14 MS. THOMAS: Mm-hmm.

15 MR. SOLTANI: But you can make it very
16 difficult for people to vote. I mean, we've
17 historically seen people putting voting booths in
18 places that are difficult for consumers to go to -- for
19 voters to go to, it reduces the rate at which certain
20 populations will vote, right?

21 And I feel like this kind of butts up against
22 that. When you make it slightly difficult for people
23 to do a particular outcome -- and sure, absolutely, you
24 can call, you can scour the internet, you can research
25 and find other offers, but we know most people don't

1 call. Most people take the offers they're given and
2 put some amount of credit in -- they put some amount of
3 effort in their busy lives to do a set of activities,
4 one of which is try to research a credit card and take
5 the best deal that their search engine gives them.

6 MS. ARIAS: Why don't we have -- I think Joe
7 hasn't spoken for a bit. Why don't we have Joe maybe
8 jump in and then we can have Claudia.

9 MR. TUROW: I wanted to kind of pick up to
10 where Ashkan was coming from. Putting it into broader
11 historical perspective, I think we're really at a very
12 different point in terms of how we understand pricing
13 and what it all means.

14 I think if you look historically at the U.S.
15 retailing situation, the 19th and 20th century was
16 about the progressive, relatively speaking,
17 democratization of prices. You could walk into a store
18 and pretty well you would see the prices. Of course,
19 some people got different prices, some people went into
20 a back room. But generally speaking, prices became,
21 for lots of interesting reasons, democratized.

22 We are moving away from that ideal in very
23 interesting ways. And not just in the online or mobile
24 space, but brick-and-mortars now change the prices by
25 the hour and change the prices by the person. So

1 literally, you could be walking through a store and the
2 prices would be different for you, particularly with
3 the new, you know, Apple and Bluetooth situation, where
4 you walk through the store and it actually knows who
5 you are. That's a very different way of thinking about
6 the world.

7 And I think -- so there are some really,
8 really important issues like financial and health, but
9 in the broader sense of how we are going to see one
10 another and understand ourselves. If we are walking
11 through a world where we are consciously aware of, for
12 reasons we have no idea, we are getting different
13 offers, different deals, different understandings of us
14 based upon calculations of our lifetime value, which is
15 five years, by a retailer, that we have no idea why it
16 came? That's a different mindset of how we understand
17 the world.

18 And people are going to have to catchup with
19 that. I think most of us are still in the 20th century
20 and there may be good reasons why we're encouraged to
21 be in the 20th century thinking about this. But the
22 world is changing so drastically, it really creates
23 incredible tensions.

24 MS. PERLICH: I actually really, really like
25 that, because that's the direction I was thinking about

1 as well.

2 I think there are two questions. One, are
3 you comfortable with the brave new world of this kind
4 of differential pricing? The question is, what role
5 does alternative scoring play? Honestly, what Ashkan
6 presented, it's not about alternative scores, it's
7 about the big picture of using data. There isn't even
8 a score. I mean, it's a flag on my user-agent. If you
9 really want to make every single data point a score,
10 then that would be infinite, you can't govern that.

11 He was really talking about the use of single
12 data points. That's very different from the question
13 of well-defined scores that are aggregates or even what
14 I presented. My models would charge rich people more
15 because they are more likely to buy at higher prices
16 than poor people. So his findings are a human
17 decision. There was an expert that thought, those guys
18 must be rich, let's charge them more. There wasn't a
19 model involved. It's the singular use of data points.

20 MR. SOLTANI: That's actually not true. So
21 in the user-agents, sure, but in the credit card
22 offers, remember X+1 was -- it determined, by some
23 scoring, whether you -- your credit profile, for
24 example. It would determine -- or the location, right?
25 So the location would determine, based on some other

1 factors, a score which is your distance to a
2 competitor.

3 MS. PERLICH: I'm just saying it's a range.

4 MR. SOLTANI: For sure.

5 MS. PERLICH: It goes from a single data
6 point all the way to these aggregate scores that --

7 MR. SOLTANI: Absolutely. Just clarifying.

8 MS. PERLICH: Yeah.

9 MS. ARMSTRONG: Joe, we talked earlier in
10 some of our conversations -- oh, I'm sorry, Ed.

11 MR. MIERZWINSKI: Yeah. I just wanted to say
12 that the issue -- I do care a great deal about the Fair
13 Credit Reporting Act, but when we don't cross that line
14 of determining eligibility or whatever, I care about
15 the scores on the far side of the line.

16 I agree the FTC has done a good job with
17 companies that have crossed the line, by selling
18 information about your friends on Facebook or other
19 social network sites that bears on your reputation and
20 makes you a credit reporting agency. Good stuff.

21 But on the other side of the line, a lot of
22 these credit card sites that you go to to find the best
23 deal are actually what are called -- and I can't
24 believe -- I don't think this term has been used yet
25 today, lead-generation sites. And lead-generators

1 auction you off, in realtime, not to the lowest or the
2 best bidder for you, but to the highest bidder. And
3 you have no idea, it's a completely nontransparent
4 process.

5 Now sometimes they may send you to CapOne,
6 in the credit card case, sometimes they may send you to
7 a third-tier credit card company, but the lead-gen
8 sites are also primarily used by the bad guys on the
9 internet. The online payday lenders, the for-profit
10 schools, and others.

11 And again, they are paying, based on all the
12 information they collect about you, for a score that
13 makes you someone that they can take advantage of. And
14 that needs to be looked at. And fortunately, the
15 states of New York and Illinois and other states, plus
16 the CFPB and the FTC are looking into this. But it's a
17 very important area, scores that are outside of the
18 FCRA. When we get to a world where the FCRA is small
19 and these other scores are big, that's a bad -- that's
20 a bad world.

21 MS. DIXON: I think we're already at that
22 world. And I want to go back to the point I made about
23 the Klout score.

24 So in the report that we have forthcoming, we
25 describe a gentleman who was denied -- actually, he

1 lost a job offer and was told he was denied because his
2 Klout score was deemed too low.

3 So it caused us to do a thought experiment,
4 is Klout a CRA? And we had to come to the answer that
5 it is not. Otherwise, every single entity on the
6 planet would be a CRA. So we have to also apply First
7 Amendment issues to this. There's a huge tension. We
8 can't make everyone who uses a piece of data for
9 eligibility reasons a CRA.

10 So given that, what do we do? And that's
11 what I'm saying. And I think we really need to have
12 transparency as an important first step. No secret
13 factors, no secret scores. Tell people what's
14 happening and then let's start figuring things out.

15 MS. ARMSTRONG: Thank you, Pam. Joe, I
16 wanted you to take a little bit more time to speak
17 about the future. I mean, how do you see some of these
18 scores being used in the social, in the mobile, and
19 other contexts?

20 MR. TUROW: Well, if we think about scores
21 broadly, meaning indexes of how people act and
22 predictive analytics, in terms of where they will go,
23 my sense is that it simply has to become more and more
24 pervasive. And the reason I say that is because of the
25 hyper-competition that exists.

1 We're in a world today where the meeting
2 between brick-and-mortar and the online world is so
3 competitive. When you're competing with Amazon, that
4 doesn't worry about margins, for example, seemingly,
5 that raises lots of interesting questions.

6 And essentially I see it as mobile,
7 wearables, and even cars. We're going to be in a
8 situation where our car will be part of our
9 decision-making and the decision-making about us.
10 We'll be in situations where -- it is possible, if you
11 give your permission, for cameras to look at your face.
12 There is a company now, Emotion, that can actually look
13 at facial features and decide certain aspects of what
14 you think, your emotions, when you're purchasing
15 something. There's a Russian company, and actually I
16 think HP has a similar thing, which can look at you at
17 check out and then try to connect you as you're moving
18 around stores and elsewhere.

19 MS. ARIAS: Joe, can you lean into the
20 microphone? We're having --

21 MR. TUROW: Oh, I'm sorry.

22 MS. ARIAS: -- trouble hearing you a little
23 bit.

24 MR. TUROW: So the idea here is that, more
25 and more, it is a question of not so much the

1 technology, but what we want to put up with. The
2 competition in the world is going to be that predictive
3 analytics is the future. I think the 21st century is
4 about data and data is incredibly important. Companies
5 have to do this and they will do it as much as they
6 can, with the idea of getting people to see that it's
7 relevant to them.

8 And thereby -- and I won't go on and on,
9 because it's a fascinating topic, but the issue of
10 relevance is at the core. And it's terribly important,
11 people want to get relevant ads. I think they want to
12 get relevant offers and relevant deals. The tension
13 that exists has to do with how do I do that, while not
14 having my data being used for things I don't even know
15 about and may not agree with. What is the seepage of
16 those data elsewhere, okay? How am I being scored that
17 may affect some other parts of my life? If I get a
18 discount that's relevant, but I give in some data,
19 well, that's terrific. I'll give you the stuff, but
20 then it gets used in ways I don't want.

21 All of these things are part of the tension
22 that we have to deal with in today's world. Everybody
23 wants relevance, the question is do they really know
24 the price of that relevance?

25 MS. ARIAS: And so I think that's an

1 excellent point, and I know we're running short on
2 time, but we really want to talk about some of the
3 solutions that folks think need to be implemented, to
4 the extent we need any.

5 So I'm going to open it up to the panel, to
6 the extent anybody has any thoughts on this. Ashkan?

7 MR. SOLTANI: So one idea might be, and this
8 is, again, pie-in-the-sky and probably a few years out,
9 if we can define the contours of the uses that we care
10 about that are kind off limits. And we're talking
11 about data and algorithms here.

12 You know, kind of like what I've put
13 together, I wonder if there's ways to do basically unit
14 tests? Test cases where you basically feed in data
15 into an algorithm, feed in populations, feed in either
16 fake users or real users or require auditing or
17 reporting of the output, of the classification, such
18 that you can audit the results and say, look, whatever
19 the data input that you have, whatever those sources
20 are, you're clustering these users based on race. Or
21 you're providing offers based on sensitive categories
22 of information that we don't want. And as a result,
23 this algorithm seems to be discriminatory.

24 It's kind of pie-in-the-sky black-boxing, but
25 it's essentially, I think -- because there are so many

1 sources of data, because there are so many different
2 algorithms, because often times the creators don't
3 explicitly -- so the examples I showed were explicit.
4 Often times, as Claudia described, it's clustering. It
5 just so happens that you cluster and you're clustering
6 based on distance from a competitor, but you also
7 happen to cluster based on race or ethnic type, just
8 because that also correlates to zip code.

9 And so if you start seeing that type of
10 behavior in the output of an algorithm, then you can
11 start saying, well, either the algorithm or the data
12 sources are problematic. Sorry, that was a little --

13 MS. PERLICH: So this isn't necessarily an
14 answer. I feel strongly that it really comes
15 ultimately down to what you do. I think we have to
16 focus on decisions that we are comfortable with making.
17 I consider that there is the pie-in-the-sky, getting
18 there is a long way from where we currently are.

19 The challenge of predictive modeling is it's
20 a reflection of the current biases of human nature.
21 It's a reflection of the fact that certain demographics
22 are in worse economic state and the model will pick up
23 on this and reflect that directly.

24 And I have a hard time making the model not
25 do that. It's very hard for me to insert my morals

1 into what just the state of the world is. My models
2 come to the point where I am making decisions based on
3 what that model tells me. I think that's, for me,
4 where I can have a judgment easier, than trying to sift
5 through the incoming and what it may or may not mean.

6 MS. ARMSTRONG: Everyone is going to have an
7 opportunity, before we end, to make a final comment,
8 but with what both Claudia and Ashkan have said, I
9 wanted to raise an issue that the recent NCLC report
10 described.

11 And it was a scenario where American Express
12 lowered the credit limits because of other customers
13 who shopped at places that consumers shopped and they
14 had a poor repayment history. And this is also
15 consistent with some of the other issues that that
16 report raised about the discriminatory impact and I'd
17 like to get some comments on that.

18 MS. DIXON: I'm concerned about cohort
19 scoring, so who your friends are kind of tells other
20 companies or entities or health care institutions who
21 you are. It's a predictive modeling validation tool.
22 However again, I come back to, we can't have secret
23 factors and secret scores. Transparency is going to do
24 a lot to ease some of this and I think we're going to
25 have to find a way to meet in the middle.

1 You have to validate the score, right? But
2 if you're validating a score in a discriminatory
3 fashion, that's a huge problem. But we're never going
4 to know about it unless someone has done some, you
5 know, some very surgical-strike research.

6 MR. PRATT: So any transaction that AmEx
7 would make relative to a portfolio of credit cards, we
8 all know it, regulated by those same laws, that
9 alphabet soup of laws we talked about before.

10 So there may be other instances that are
11 outside of the credit portfolio context where I suppose
12 you might have some conversation about, you know, the
13 effects. But in the context of a portfolio, if you're
14 going to change the contract, something about those
15 terms, you have to control for all of the current law
16 factors that are out there, ECOA, disparate impact,
17 Fair Lending, anything else that would apply to that
18 portfolio. So there's this penumbra of protection, if
19 you will, around that kind of portfolio decision.

20 We don't know whether that was a good
21 decision or not, we don't know if that was an effective
22 decision or not, we don't know if that was an
23 experimental idea in the midst of the recession, as
24 every card issuer was trying to figure out what to do
25 to measure risk, as card portfolios and, of course, all

1 financial services portfolios began to crater just a
2 little bit, you know, in terms of size of risk
3 population, which was much, much larger than had been
4 the case historically.

5 So I mean, there's a lot to think about.
6 We're getting just this little tiny anecdotal moment
7 here, but not much else really.

8 MS. ARMSTRONG: That's a good -- that's an
9 excellent point.

10 MR. MIERZWINSKI: Well, I would just say
11 briefly, that if companies do this and they do it on a
12 non-protected class discriminatory manner, they may not
13 implicate any of this alphabet soup of laws. Companies
14 like LendUp and Move-In, if that's how you say that
15 word, I've never used it before, are making decisions
16 about who to make credit offers to based on their
17 social networking status. But they're not credit
18 reporting agencies, they're simply making decisions
19 about their own customers, or potential customers, and
20 they may not be regulated.

21 So we really need to look at regulating the
22 system of scoring that isn't regulated today.

23 MS. ARIAS: And to follow-up on that, what do
24 you envision would be the way to regulate? If, in
25 fact, they are not regulated under the FCRA or any of

1 the other alphabet soup laws?

2 MR. MIERZWINSKI: Well, I think the first
3 step is really transparency of the online scoring
4 system, the graphic that Ashkan put up of all of these
5 hundreds of companies. They are all
6 business-to-business companies, nobody knows who they
7 are.

8 In the past, you knew that you had a
9 relationship with your creditor. And although you
10 didn't choose your credit bureau, you knew that you had
11 the three credit bureaus and your creditors, who you
12 could choose. But you didn't know about all of these
13 other companies out there that were providing services.
14 And that needs to be more transparent and consumers
15 need to have rights when their information is used.
16 The right to look at their profile of a data broker,
17 the right to change the profile of a data broker, and
18 the right to block the use of their information for
19 other purposes.

20 And there should be some disclosure, just
21 like there is when you are denied credit on the basis
22 of a credit report, that you're denied credit on the
23 basis of some other kind of report.

24 MS. ARMSTRONG: And with respect to
25 transparency disclosure, I'm wondering about choice for

1 consumers and whether you have an opinion about where
2 in the ecosystem the consumer choice should occur.

3 MR. MIERZWINSKI: Well, we don't have a lot
4 of time. If you're asking me, I would just say that I
5 would refer people to look at the final Commission
6 report on privacy. I think it's an excellent
7 background around all of these questions.

8 MS. ARMSTRONG: Okay. I think it's time that
9 we're going to run down this row and let everybody make
10 a final comment before we conclude. So Rachel, you're
11 first.

12 MS. THOMAS: Can we start at the other end
13 this time?

14 MS. ARMSTRONG: Or would you like to be last?
15 Okay, we can do that. Ashkan?

16 MR. SOLTANI: So one thing that I think
17 that -- sorry. One idea that we might have -- I think
18 Claudia is absolutely right that this is a difficult
19 thing to get at and to underscore. One thing that we
20 might want to do is to explore, like the FTC authority,
21 for example, when a company says, you're getting the
22 lowest price, right? And you're actually not, you're
23 getting a different price based on ratings. Or Joe is
24 getting a lower price than I am, should a company be
25 required to say, you're getting the lowest price for

1 you, based on this information? Or you're getting the
2 best credit card deal for you, based on this
3 information? Or can they just outright say, you're
4 getting the lowest price, because that seems like an
5 absolute statement.

6 And I wonder, under Section 5, if there is
7 authority to at least nudge or poke at that.

8 MS. ARMSTRONG: Or you know, we can do this
9 in any order, just as long as everybody gets to say
10 something.

11 MS. PERLICH: Well, I'm just going to skip my
12 right to have a final word here and leave it to the
13 rest of the panel.

14 MS. ARMSTRONG: Thank you.

15 MR. TUROW: I'm just going to say something
16 that may be quixotic, but we have found in survey after
17 survey, I think five times, that people think that when
18 a site has the word "privacy policy" on it, they think
19 that it means the site doesn't sell or trade
20 information without their permission. This is 56 to 62
21 percent of Americans. 75 percent don't know that, in
22 fact, it's true that they give up -- that they don't do
23 that, necessarily.

24 So the only thing I would suggest here, and
25 it's only a beginning, but it would cause an

1 interesting amount of chaos in the industry, which is
2 if a site uses your information without explicitly
3 getting your permission, it's deceptive by the FTC and
4 it shouldn't be called a privacy policy. It should be
5 called using your information. That would be an index
6 to people to be careful. It would, right off the bat,
7 say be careful.

8 If it says privacy policy, you know that
9 you're safe. If it says something else, you know to be
10 careful. And I think that would be the beginning of an
11 interesting conversation with the industry.

12 MS. DIXON: So just to roll down the line,
13 why not? So there are many new scores, many. Many, if
14 not most of these, are outside of the current
15 regulatory structure. Some of these scores are much
16 more important than others. Some are not important,
17 some are very important and the deciding factor is the
18 impact. And we are focused really on eligibility uses,
19 especially those that are happening outside of
20 regulation, and they are.

21 We'd really like a solution, a first step of
22 real transparency that's meaningful, no secret scores,
23 no secret factors. Discussions with industries, so we
24 know what's happening, and a real meaningful commitment
25 from industry to have transparency about this.

1 We'd really like for there to be oversight
2 and disclosure to the consumer about purposes,
3 composition, and uses of the important scores.
4 Probably not all of them, there's too many, but the
5 really important ones that matter.

6 MR. MIERZWINSKI: Well, although I mentioned
7 that I got a fishing catalog by mistake, I don't care
8 about that kind of marketing, if I didn't make that
9 clear. But I do think that financial information,
10 healthcare information, and information about children
11 needs to be looked at, in events like this, in greater
12 detail. I'm encouraged by events like this being held.
13 I'm encouraged that recently, it was in the press, that
14 a number of civil rights groups have developed a
15 platform on the use of big data for financial
16 opportunity.

17 And we're starting to look at this, and we
18 don't have the answers yet today, but it's encouraging
19 that were starting to create a framework of answers.

20 MR. PRATT: So for me, as the CDIA, I'm just
21 going to echo what I said at the very beginning, risk
22 management matters. It's critical, it keeps us safe,
23 and it ensures the transaction is me when it is me and
24 it ensures the transaction stops when it's not me. So
25 bank safety and soundness matters. It's important that

1 we have ways to measure risk and to rank order
2 consumers in terms of risk.

3 And just a couple of quick thoughts about the
4 glossary, and I know this is kind of nerdy stuff here,
5 but I hate the data broker term. It's a really sloppy
6 term, it wraps around all different kinds of U.S.
7 business models and it conflates issues in the public
8 policy world as well. And we've seen this, actually,
9 in legislation that's been introduced on the Hill. So
10 it's just a crummy term. And I suppose if I could get
11 out my big eraser, I'd erase the term data broker and
12 we would try to parse through the issues in a little
13 more refined way.

14 Get rid of the term score. The only reason I
15 advocate for that is because it's too often conflated
16 with credit score, too often conflated with what
17 consumers now think of as a credit score. So again,
18 this is just sort of marketing stuff. If we're
19 communicating with consumers through venues like this,
20 we ought to pick terms that make sense to consumers.

21 I think, Joe, your term about using my data
22 versus privacy is the kind of example that pivots off
23 of that same idea. Using my data is different than,
24 you know, privacy, which may be a more amorphous term
25 that we don't understand or connect with as much.

1 By the way, the problem with data brokers is
2 it really doesn't -- you know, it kind of lumps
3 together first party third party. We don't think
4 those issues matter very much. Our members are
5 third-party databases, dataflows have to come to
6 third-party databases. It's how the American economy
7 operates. Dataflows are necessary, I agree with what
8 Joe said. Dataflows are going to occur, we're going to
9 be in a highly competitive environment. I do think
10 that what Joe said is right, consumers -- by the way,
11 I'm going to add to what Joe said. I think consumers
12 will catch up a bit, will begin to become smarter
13 consumers, even in an environment where competition has
14 ebbed, you know, changed a little bit over time.

15 So we should be encouraged. These dataflows
16 can ultimately open doors for us that weren't open
17 before, they can include us when we were excluded
18 before, they can give us better offers that save us
19 money. It's still up to us, as consumers, to do some
20 shopping in the context of all that.

21 MS. THOMAS: So we've touched on some
22 examples today, some of which, you know, at the end of
23 the day, it sounds as though they are covered by FCRA,
24 some maybe there are still questions about whether
25 they're covered or they aren't.

1 But I think it's important to recognize that
2 if we're focusing today on some difficult areas, there
3 are a lot of areas that we are not concerned about,
4 right? The dataflows are happening. Data is data is
5 data. What we need to be concerned about is particular
6 uses. Thank you for focusing us in that way today.

7 But I think it's also really important to
8 recognize that the reason there are so few things that
9 we have reason to be concerned about is because
10 companies are making sure -- companies, nonprofits, all
11 of the above, have strong incentives to self-regulate
12 and not do bad things to their customers on a daily
13 basis. And that there is DMAs, as well as many other
14 self-regulatory environments, that are making sure
15 that, if there are areas where the law doesn't cover,
16 and there are so many laws that we discussed today that
17 do, but in those areas, businesses are doing the right
18 thing because they are being held to standards by
19 organizations like DMA. And if they aren't meeting
20 those standards, we know where to find the FTC and we
21 do refer them over, as needed, to the FTC or other law
22 enforcement.

23 At the end of the day, we need to enforce
24 what we have, whether it's through self-regulation of
25 the laws that we've got, and continue to make sure that

1 data is used responsibly in both of those areas.

2 MS. ARMSTRONG: Thank you very much. And
3 we'll continue down the line for our last few comments
4 and then call it a morning.

5 First of all, I appreciate everybody coming.
6 I wish we had more time, this was fascinating. We are
7 accepting public comments about today's -- on these
8 issues until April 19th. And thank you very much for
9 everyone who sent a question card. I know we didn't
10 get to everything, but we are thinking about these
11 things.

12 And finally, I wanted to remind everybody
13 about the next installment of our Spring Privacy Series
14 on May 7th, which will focus more on health-type
15 products.

16 MS. ARIAS: And just to finish everyone off,
17 I really want us to pause for a second and thank this
18 great, great panel.

19 MS. ARMSTRONG: Fabulous.

20 MS. ARIAS: Fabulous, that's right.

21 MS. ARMSTRONG: Fabulous.

22 MS. ARIAS: If we can applaud them, they did
23 what we thought was unthinkable today, which is cover a
24 really, really broad subject, cover lots and lots of
25 issues, and really touch and started the conversation,

1 so I really want to thank them.

2 But I want to thank you, our audience, and
3 everyone out in the internet, watching us on the
4 webcast, you've really been a fabulous audience and we
5 really look forward to your comments and suggestions on
6 this topic.

7 Thank you everyone.

8 (Whereupon, the proceedings
9 concluded at 12:05 p.m.)

10

11

12

13

14

15

16

17

18

19

20

21

22

23

24

25

1 C E R T I F I C A T I O N O F R E P O R T E R

2

3 MATTER NUMBER: P145401

4 CASE TITLE: SPRING PRIVACY SERICS

5 DATE: MARCH 19, 2014

6

7 I HEREBY CERTIFY that the transcript contained herein
8 is a full and accurate transcript of the notes taken by me
9 at the hearing on the above cause before the FEDERAL TRADE
10 COMMISSION to the best of my knowledge and belief.

11

12 DATED: MARCH 27, 2014

13

14

15 STEPHANIE GILLEY

16

17 C E R T I F I C A T I O N O F P R O O F R E A D E R

18

19 I HEREBY CERTIFY that I proofread the transcript for
20 accuracy in spelling, hyphenation, punctuation and format.

21

22

23

24 SARA J. VANCE

25