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FEDERAL TRADE COMMISSION

BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION

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Big Data: A Tool for Inclusion or Exclusion

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1 P R O C E E D I N G S

2 MS. GEORGE: Good morning. Good morning,
3 everyone. It's a few minutes after 9:00, so we're going
4 to go ahead and get started. Please take your seats.

5 Good morning, again. My name is Tiffany George
6 and I am an attorney here at the Federal Trade
7 Commission. Welcome to the FTC Workshop Big Data: A
8 Tool for Inclusion or Exclusion. Before we get started I
9 have a few housekeeping items to cover. Anyone who goes
10 outside the building without an FTC badge we will be
11 required to go through the magnetometer, an x-ray
12 machine, prior to reentering into the building.

13 In the event of a fire or evacuation of the
14 building please leave the building in an orderly fashion.
15 Once outside of the building, you need to orient yourself
16 to Constitution Center. Across from the FTC is the HUD
17 building. Look to the right front sidewalk. That is our
18 rallying point. Everyone will rally by floors. You need
19 to check in with the person or persons accounting for
20 everyone in the auditorium. In the event that it is
21 safer to remain inside, you will be told where to go
22 inside the building. If you spot suspicious activity,
23 please alert security.

24 This event may be photographed, videographed,
25 webcast or otherwise recorded. By participating in this

1 event you are agreeing that your image and anything you
2 say or submit may be posted indefinitely at ftc.gov or on
3 one of the Commission's publicly available social media
4 sites.

5 The Seasons Cafeteria is located inside this
6 building and the operating hours are from 7:30 a.m. to
7 3:00 p.m. Please note that there are no food or
8 beverages allowed inside the auditorium. Also, please
9 remember to silence your devices.

10 And with that, now I'd like to introduce our
11 FTC Chairwoman, Edith Ramirez, who will make some opening
12 remarks.

13 (Applause.)

14 OPENING REMARKS

15 CHAIRWOMAN RAMIREZ: Thank you, Tiffany, and
16 welcome everyone to our new facility, those of you who
17 haven't been here before. I want to thank everyone for
18 joining us here today for our workshop Big Data: A Tool
19 for Inclusion or Exclusion. And I also want to take this
20 opportunity to thank Tiffany George, as well as all of
21 the other FTC staff members who have worked so hard to
22 organize today's event, and also to thank the speakers
23 for sharing their expertise with us.

24 We are at a pivotal stage in the Information
25 Age. Thanks to smart phones and smart meters, wearable

1 fitness devices, social media, connected cars and retail
2 loyalty cards, each of us is generating data at an
3 unprecedented rate. In 2013 it was reported that an
4 astonishing 90 percent of the world's data was generated
5 in the two preceding years. Today, the output of data
6 is doubling every two years. Advances in computational
7 and statistical methods mean that this mass of
8 information can be examined to identify correlations,
9 make predictions, draw inferences and glean new insights.
10 This is big data. It has the capacity to save lives,
11 improve education, enhance Government services, increase
12 marketplace efficiency and boost economic productivity.

13 But the same analytic power that makes it
14 easier to predict the outbreak of a virus, identify who
15 is likely to suffer a heart attack, or improve the
16 delivery of social services, also has the capacity to
17 reinforce disadvantages faced by low-income and
18 underserved communities. As businesses segment consumers
19 to target what products are marketed to them, the prices
20 they are charged, and the level of customer service they
21 receive, the worry is that existing disparities will be
22 exacerbated. Is this discrimination? In one sense,
23 yes. By its nature that's what big data does in the
24 commercial sphere. It analyzes vast amounts of
25 information to differentiate among us at lightning speed

1 through a complex and opaque process.

2 But is it unfair, biased or even illegal
3 discrimination? And if so, can steps be taken to level
4 the playing field? Those are the questions we'll be
5 exploring today. Big data in its 21st Century form is in
6 an early stage. We have the ability to shape its
7 development and its outcomes. If we're alert to the
8 risks presented by big data we can take steps to guard
9 against them. We can help ensure that big data can be a
10 tool for economic inclusion, not exclusion. That's the
11 weighty subject before us today.

12 But before we begin the discussion, I'd like to
13 address three questions. First, how did we get here?
14 Second, what's our aim with today's program? And
15 finally, where do we go from here?

16 Let me start by tackling the first question,
17 how did we get here, very literally. Whatever mode of
18 transportation you used to get to this workshop, there
19 were apps or connected devices available to assist your
20 commute. Those of you who came here using public
21 transportation may have availed yourselves of apps to
22 tell you when the next bus or train would arrive. If you
23 came by car, you may have benefitted from GPS
24 technologies that gave you directions, sent you realtime
25 traffic alerts, or allowed you to summon a taxi or driver

1 by tapping on a smart phone app. And for the virtuous
2 among us who biked or walked here, you may have used a
3 wearable device to track the distance traveled and
4 calories burned. No matter your mode of transportation,
5 once in the vicinity, an app or website may have helped
6 you to find a spot nearby to buy a cup of coffee before
7 arriving at the workshop.

8 These very devices and services that help many
9 of us get here physically are also what brought us here
10 figuratively. The popularity of smart phones and other
11 mobile devices, the array of mobile apps we have at our
12 fingertips, and the burgeoning internet of things
13 phenomenon more generally means that countless
14 individuals actively and passively generate information
15 in an extensive ecosystem throughout the day.

16 The proliferation of connected devices, the
17 plummeting cost of collecting, storing, and processing
18 information, and the ability of data brokers and others
19 to combine offline and online data means that companies
20 can accumulate virtually unlimited amounts of consumer
21 information and store it indefinitely. Using predictive
22 analytics, they can learn a surprising amount about each
23 of us from this data.

24 While powerful algorithms can unlock the value
25 from immense data sets, their ability to draw

1 correlations and make fine grain distinctions also raises
2 the prospect of differential treatment of low-income and
3 underserved populations. This is a risk suggested by the
4 Commission's recent report on the data broker industry,
5 the Commission's study of the cross section of nine data
6 brokers, that data brokers aggregate online and offline
7 data from disparate sources to make inferences about
8 consumers' ethnicity, income, religion, age and health
9 conditions among other characteristics.

10 As the FTC and others have found, some brokers
11 create segments or clusters of consumers with high
12 concentrations of minorities or low-income individuals.
13 There may be legitimate reasons why businesses would want
14 to sort consumers in this fashion, but the practice also
15 raises the possibility that these segments will be used
16 for what I've called discrimination by algorithm, or what
17 others have called digital redlining.

18 We heard these concerns this past spring at the
19 FTC seminar on predictive scoring. There are now
20 products beyond traditional credit scores that purport to
21 predict or score everything from the chances that a
22 transaction will result in fraud to the efficacy of
23 sending consumers catalogs and the best prices to offer
24 consumers. Some speakers lauded the benefits of such
25 predictions, emphasizing that they enable the

1 personalization many consumers want and help minimize the
2 risk of fraud. But other speakers worried that certain
3 predictive scoring products could fall outside the reach
4 of the Fair Credit Reporting Act and the Equal Credit
5 Opportunity Act, despite having an impact on consumers'
6 access to credit, housing, employment and insurance.

7 For example, if a company lowers my credit
8 limit based on a score that reflects my own credit
9 history, I would be entitled to certain protections under
10 the FCRA. If, however, the same company lowers my credit
11 limit based on the scores of a group of which I am a
12 member, the application of the FCRA may be less clear.
13 Will these scores be used in ways that influence the
14 opportunities of low-income, minority, or other
15 populations to get credit, jobs, housing or insurance in
16 ways that fall outside of the protections of the FCRA or
17 ECOA? Could the use of geographic information, such as
18 zip codes, for example, lead to Americans in low-income
19 or rural neighborhoods being charged higher prices? And
20 if so, is this a worrisome function of big data or a just
21 a continuation of age-old pricing practices and market
22 forces?

23 These and other issues figured prominently also
24 in the White House's wide-ranging report on big data,
25 which squarely raised the concern that large-scale

1 information analytics will be used for disparate or
2 discriminatory outcomes for certain consumers, even
3 absent discriminatory intent. It's these questions and
4 concerns raised by these prior initiatives that bring us
5 to today's program and to my second question, what is our
6 goal today?

7 We'll explore whether and how big data helps to
8 include or exclude certain consumers from full
9 opportunity in the marketplace. And to help shed light
10 on these issue we've convened experts from industry,
11 consumer, and civil rights groups, academia and
12 government, all of whom are representing a wide variety
13 of perspectives. Our panelists and speakers will provide
14 us a framework for our conversation today, assess current
15 big data practices in the private sector, discuss
16 possible developments on the horizon, present pertinent
17 research and offer potential ways to ensure that big data
18 is a force for economic inclusion. It's my hope that our
19 participants will discuss in depth the benefits and risks
20 of big data to low-income and underserved populations.

21 On the benefits side, let me start the
22 discussion with one example. New York City is developing
23 a tool that combines eviction data with emergency shelter
24 admission information and other data to predict when
25 individuals or families are on the brink of homelessness.

1 Using this information, the city is able to deploy social
2 workers to help these families and prevent them from
3 ending up on the street. This is an example of positive
4 government use, rather than a business use, but I hope
5 our speakers -- our speakers will provide examples
6 showing how companies can also use big data to benefit
7 those in low-income or underserved groups.

8 And as for real world examples of possible
9 risks, let me cite a study conducted by Latanya Sweeney,
10 who's here from Harvard serving as the Commission's Chief
11 Technologist. Professor Sweeney found that web searches
12 for distinctively black names were 25 percent more likely
13 to produce an ad suggesting the person had an arrest
14 record, regardless of whether that person had actually
15 been arrested, than web searches for distinctively white
16 names.

17 This could have devastating consequences for
18 job applicants and others by creating the impression the
19 individual has been arrested. While the research did not
20 establish why the algorithm yielded these racially
21 disparate results, it does provide a concrete example of
22 how an algorithm may have adverse repercussions for a
23 particular population. I expect we'll hear more
24 illustrations today, including from Professor Sweeney who
25 will be presenting results of a more recent study.

1 After we conclude our workshop, the question
2 naturally arises, where do we go from here? We may all
3 have an array of apps to guide us home when we leave this
4 afternoon, but there's no clear path for navigating the
5 use of big data in a way that advances opportunities for
6 all consumers while diminishing the risks of adverse
7 differential impact on vulnerable populations.

8 We may not yet know what the best course ought
9 to be, but I believe we should have at least three
10 objectives going forward. First, we should identify
11 areas where big data practices might violate existing
12 law. Where they do, the FTC is committed to vigorous
13 enforcement of the law as demonstrated by cases such as
14 our recent action against Instant Checkmate, a website
15 that promoted some of its background checks as tools for
16 screening tenants and employees. The FTC alleged that
17 Instant Checkmate did so without regard for the FCRA, and
18 we obtained a \$525,000 fine and a permanent injunction
19 against the company. In addition to helping the FTC and
20 others to enforce existing laws, today's program should
21 also help identify any gaps in current law and ways to
22 fill them.

23 Second, we need to build awareness of the
24 potential for big data practices to have a detrimental
25 impact on low-income and underserved populations. I'd

1 like today's program to help foster a discussion about
2 industry's ethical obligations as stewards of information
3 detailing nearly every facet of consumers' lives.

4 Third, and relatedly, we should encourage
5 businesses to guard against bias or disparate impact on
6 low-income and vulnerable populations when designing
7 their analytic systems, algorithms, and predictive
8 products. A good example is the Boston Street Bump App
9 highlighted in the White House Big Data Report. Like any
10 big city, Boston has its share of potholes and faces the
11 ongoing challenge of staying on top of street repairs.
12 To help address the issue, the city released a mobile app
13 residents could use to identify potholes in need of
14 repair.

15 But the city also recognized that because lower
16 income individuals are less likely to carry smart phones,
17 the data might skew road services to higher income
18 neighborhoods. They addressed this problem by issuing
19 the app to road inspectors who service all parts of the
20 cities equally and used the data gathered from the
21 inspectors to supplement what they received from the
22 public. This illustrates how considerations of risks
23 before launching a product or service can help avoid
24 them.

25 So, big data can have big consequences. Those

1 consequences can be either enormously beneficial to
2 individuals in society or deeply detrimental. It will
3 almost certainly be a mixture of the two, but it's the
4 responsibility of the FTC and others to help ensure that
5 we maximize the power of big data for its capacity for
6 good while identifying and minimizing the risks it
7 represents. As we navigate the transformative terrain of
8 big data, it's vital that we work to ensure that
9 technological innovation benefits all consumers whatever
10 their backgrounds.

11 I look forward to hearing the thoughts and
12 ideas of our panelists on how to do just that. And I
13 thank you all for your contributions to that endeavor.
14 Thank you.

15 (Applause.)

16 CHAIRWOMAN RAMIREZ: Let me hand it back to
17 Tiffany.

18 MS. GEORGE: Thank you, Chairwoman.

19 We'll now begin with our first presentation,
20 Framing the Conversation, which will be lead by Solon
21 Barocas, a Post Doctoral Research Associate at the
22 Princeton University Center for Information Technology
23 Policy.

24 PRESENTATION: FRAMING THE CONVERSATION

25 MR. BAROCAS: Good morning. Let me begin by

1 saying how thankful I am to be here. I really appreciate
2 the opportunity to speak with you all. And I
3 particularly want to thank Katherine and Tiffany for
4 putting together what I think will be an excellent day.
5 I am Solon Barocas. I'm a post-doctoral fellow at the
6 Center for Information Technology Policy at Princeton,
7 and I will be presenting today what I hope will be a way
8 of framing the conversation today and hopefully going
9 forward as well. This draws on some of the work that
10 I've been doing, and I encourage people who are
11 interested in what I'm presenting to take a look at my
12 website where you can find this paper if you want to
13 follow along while I present in more detail.

14 But let me begin. Okay. So, big data -- we've
15 come, I think, to know the three Vs as a common
16 definition. That the volume of data is exploding, that
17 the velocity at which the data is accumulated is
18 increasing, and the variety of formats of data is also
19 likewise proliferating. This is a useful definition, but
20 I tend, I think, to focus instead on the traditional
21 categories from the social sciences, observational data,
22 what we might call self-reported or user-generated data,
23 and experimental data.

24 And what I mean by this, then, is that there
25 are actually three valid, different things happening

1 here, all of which have interesting consequences for
2 consumer protection. One is that there are many more
3 ways to actually observe consumers and consumer behavior,
4 things like transactional data, but of course, we can now
5 think of things like mobile phone and various health
6 devices, self-reported and user-generated data being the
7 vast variety of social media that people use. And
8 finally, experimental, which I think has now become
9 slightly more familiar to people in the wake of this
10 Facebook experiment that got a fair amount of press. And
11 what I mean by that is there are now platforms upon which
12 to perform large-scale experiments in the wild in ways
13 that were basically impossible before. And I think these
14 are the useful ways, perhaps, to think about it.

15 For our purposes today, however, I'm going to
16 focus on data mining, this is the more traditional term
17 from industry and the academy, which is in some ways what
18 we might call a subfield to machine learning, which is a
19 -- a kind of field within computer science that is
20 devoted to the automated computational analysis of large
21 data sets. And again, I focus on this, in part, because
22 I think for our purposes today it is the analysis and use
23 of the data that is interesting, perhaps less so the
24 technical challenges that large data sets present to
25 those who accumulate them. So, the remainder of my talk

1 will focus specifically on the analytic techniques and
2 why those analytic techniques present some kinds of
3 trouble for us when thinking about consumer protection.

4 So, what I'll say then as a kind of starting
5 place that we can define data mining as the automated
6 process of extracting useful patterns from large data
7 sets, and in particular, patterns that can serve as a
8 basis for subsequent decision making. You can -- I'm
9 saying here in quotes "learning," meaning I learned from
10 the previous examples that there is some general trend,
11 some relationship in the data that I imagine will hold
12 true in the future and I can use that as a way to make
13 future guesses and inferences as mentioned earlier
14 already.

15 For terminology, I thought I'd also point out
16 that within the field this accumulated set of
17 relationships within the data is commonly referred to as
18 a model. So, you might have heard the term predictive
19 model. What that refers to, then, is all the various
20 kinds of patterns that have been extracted from the large
21 data set that then inform future decision making. And
22 this model can be used in a variety of ways.

23 To begin with it can be used to classify
24 entities. So, the most common example of this would be
25 spam. I think many people are familiar with this. Your

1 computer often, webmail in fact, will make guesses about
2 whether or not your message is spam or not, and again, it
3 arrives at a rule to determine what is spam and what is
4 not spam based on the history of examples of spam it has.
5 Likewise, it can estimate values of unobserved
6 attributes, or it can guess your income, for instance, as
7 also mentioned. And finally, it can also make
8 predictions about what you're likely to do. So, future
9 consumer behavior of all sorts.

10 Now, you might say, as again was already
11 mentioned, that, of course, data mining is
12 discriminatory. The very intent and purpose of the
13 activity is to be able to differentiate and draw
14 distinctions. And what I would say, too, is that it is
15 in some sense a statistical form of discrimination that
16 is almost by necessity a rational form because it is
17 being driven by apparent statistical relationships. And
18 the data -- these are not arbitrary or this is not a case
19 of caprice; this is, in fact, evidence suggesting that
20 there are reliable patterns to the data. And using that
21 you can confer to the individual those qualities which
22 happen to be similar to those who appear statistically
23 similar. So, if I reside in one particular statistical
24 category that has been revealed by the analysis, they can
25 impute to me those same qualities.

1 So, the remainder of the talk will focus on
2 this five-part taxonomy, which is me basically trying to
3 explain how the process of actually mining data lends
4 itself to a variety of issues that can raise concerns
5 with discrimination and fairness. So, let me jump right
6 into it.

7 Again, a technical term is "target variable."
8 What this basically refers to is when I set about trying
9 to determine if there are useful patterns that correlate
10 with some outcome, I need to be very specific about what
11 I mean by the outcome. So, when I am looking for good
12 customers, I actually need to arrive at a formal
13 definition of what good customer means. Does good
14 customer mean that it is the one from whom I can extract
15 the most profit? Is it the one I can have a long-term
16 relationship with? Is it the one that if I provide some
17 inducement will stay a customer? And there's no way to
18 actually avoid this formalization process. You must
19 specify in some definable way what it is that you are
20 looking for. And so the exercise of mining data always
21 begins with actually having to establish some translation
22 from a business problem into a problem that can be solved
23 by predicting the value of this target variable.

24 And in general, the art of data mining -- the
25 kind of creative work of data mining involves this

1 process of translation, finding a smart, clever way of
2 actually translating some kind of business problem into
3 one that can be solved by predicting the target variable,
4 by inferring the value of the target variable. And I
5 think here's what's interesting is that the way that the
6 business goes about defining the target variable can have
7 serious consequences for whether or not the data mining
8 process has a disparate impact.

9 In my own work I look at employment, and you
10 might say that trying to predict whether or not someone
11 is going to be particularly productive as compared to
12 predicting whether or not that we're going to remain a
13 customer -- rather, an employee for a set period of time,
14 trying to avoid turnover, for instance. Those
15 differences and definitions will have very different
16 consequences for how you rank potential applicants. And
17 the same would likewise be true with consumers.

18 The second part of the taxonomy is what, again,
19 data miners refer to as training data. Training data is
20 the large set of information that you use to extract some
21 kind of useful rule. It is the set of examples that you
22 look at in order to decide if there are actually useful
23 patterns to guide future behavior, future decision
24 making. And I think, in this case, there are really two
25 different, although related, problems with training data

1 that again can have consequences for fairness. One is
2 that, as also mentioned, that the -- the set of examples
3 can be skewed in some way. And the second, that the
4 examples that you draw on could actually be in some way
5 tainted by a prior prejudice.

6 So, let me try to walk through this a bit.
7 When trying to derive some general rule from a set of
8 particular examples, the only way that rule will actually
9 generalize to future cases is if the particular set of
10 examples happens to be representative of future cases.
11 And as we know from Latanya Sweeney's work, this main --
12 rather, from the Street Bump case, we know that this is
13 not always the case. And, even more interestingly I
14 think, often times companies are in the position of -- are
15 often seeking ways to try to change the composition of
16 their customer base such that to suggest that you can
17 draw general rules from what customer base that you are
18 purposefully changing, again, to put into doubt the idea
19 that this is representative data; that, in fact, you're
20 dealing with a subset of all possible customers, and the
21 particular subset you're dealing with changes over time.

22 We could also point out, I think, that the
23 reason why data is unlikely to be particularly
24 representative in certain cases, that is for reasons
25 having to do with the following. So, to begin with, it

1 might well be that certain populations are less involved
2 in the formal economy and their various mechanisms in
3 producing these kinds of digital traces. They might have
4 unequal access to -- and less fluency in the technology
5 that's required to produce those kinds of digital traces.
6 And finally, they simply might be less profitable or in
7 poor constituencies and, therefore, not the subject of
8 ongoing observation.

9 And I think that the serious problem here is
10 that often times the under or over representation of
11 particular populations is not always evident. Sometimes
12 when a geographic distribution is skewed in some obvious
13 way, as in Street Bump, we might have intuitions that, in
14 fact, there is a problem, but many times it will be much,
15 much more difficult.

16 Finally, you could also say, then, that when
17 you have this skewed example, it also suggests that
18 companies should be devoting their attention to some
19 populations and not others. And over time this can have
20 a compounding effect where certain populations are
21 discounted further and further because you have less and
22 less opportunities for those populations to disprove your
23 sense that they are not, in fact, good customers. You
24 are in fact, limiting the opportunities to buck the
25 apparent trend. And this is a serious problem in credit

1 scoring where the industry has long worked on problems
2 trying to deal with that.

3 Labeling examples. This is the process of
4 actually trying to specify what is, in fact, a good
5 customer and what is, in fact, a bad customer from
6 examples. So, I mentioned the example of spam. Let me
7 actually jump to this example. So, during the debates
8 leading up to the Equal Credit -- Equal Opportunity -- no
9 -- Equal Credit Opportunity Act, Fair Isaac pointed out
10 in those congressional debates that in fact any way of
11 drawing some rule about how to extend credit to customers
12 that looked to previous ways that consumers were
13 evaluated as potential customers of credit would simply
14 reproduce any prejudice involved in those past decisions,
15 meaning Fair Isaac could not simply draw on the history
16 of credit decisions to automate the process; it actually
17 had to find new ways to decide what, in fact, is a good
18 target for credit. And what this reveals, then, is that
19 any decision that uses past uses as a basis for inferring
20 rules must be sensitive to the fact that those decisions
21 might be tainted by prejudice in some way.

22 Finally, in this same theme, along the same
23 line, we can point out then that it's not only the case
24 that data mining can inherit past prejudice, but it can
25 continue to reflect the persistence of prejudice in the

1 behavior, taken its input to some kind of model, and
2 this, I think, is a way of categorizing some of the work
3 that Latanya Sweeney and others have done showing then
4 that if the input the algorithm receives is itself biased
5 or prejudiced in some way it will simply be reflected back
6 in the recommendations of that system.

7 Feature selection. This is the process of
8 deciding what variables, what criteria associated with
9 each person will you actually fold into your analysis.
10 And here again, I think this is an interesting issue
11 because you would imagine that big data presents
12 opportunities to vastly increase the amount of features
13 and variables you consider. Of course, these -- of
14 course, the addition of the -- adding additional features
15 to the analysis can often be costly.

16 And it may well be that your analysis does very
17 well when considering a certain set of features, but it
18 doesn't do particularly well for some populations because
19 it doesn't actually carve out the population in a
20 particularly precise way. Redlining is the traditional
21 example of this. Using neighborhood alone as a way to
22 decide who is worthy of credit is an extremely coarse way
23 of making that determination. And I think those same
24 kinds of problems can actually translate to this new area
25 because it is still possible that additional data would

1 be useful in drawing distinctions for particularly
2 marginalized populations that simply might just be very
3 costly. It might be very difficult to obtain that
4 information. And the question therefore becomes, I
5 think, does it justify subjecting these populations to
6 less accurate determinations simply because it actually
7 costs additional money or resources to gain that kind of
8 information?

9 This fourth point of the taxonomy is what we
10 call proxies. And what this refers to is the fact that
11 often times many of the features that are legitimately
12 relevant in making some kind of predictions about
13 customers might also be highly correlated with their
14 class membership, meaning certain features, certain
15 attributes, are both proxies for the thing you care about
16 and proxies for the person's class membership.

17 And what's worrisome here, then, is that it may
18 well be this is actually simply reflecting the fact of
19 inequality in society, and it's a particular form of
20 inequality where members of historically marginalized and
21 protected classes are disproportionately in a less
22 favorable position. And big data is in the position
23 potentially to simply further expose the exact extent of
24 that inequality.

25 I will, in the interest of time, jump over

1 this. The final part of taxonomy is masking, which
2 refers to the idea that it is possible to mask
3 intentional discrimination by relying on any of the
4 number of ways I've identified here of having
5 discrimination happen unintentionally. Decision makers
6 additionally can rely on data mining to infer whether or
7 not you belong to a protected class and then to use that
8 information in secret to discriminate against you.

9 I want to emphasize, though, and this is I
10 think one of the most important points I'll make today,
11 is that unintentional discrimination of this sort
12 identified in the first four parts of the taxonomy is far
13 more likely to be occurring, and it has potentially far
14 more consequences than the kinds of intentional
15 discrimination that could be pursued through masking.

16 And I'll simply conclude by saying that I think
17 there's a serious issue here about the unintentionality
18 of the discrimination that might be occurring. And in my
19 own research I have looked at Title VII and in employment
20 decisions, and my sense actually is that this aspect of
21 the problem, the unintentionality of the problem will
22 pose serious issues for trying to bring to bear legal
23 remedies. It's unclear that we have the tools when
24 looking at existing laws to actually address this form of
25 unintentional discrimination.

1 Additionally, if the problem is that we are
2 exacerbating inequality, it's also unclear whether or not
3 using discrimination laws as a way to deal with that
4 issue is the correct mechanism.

5 And finally, I think for many of the kinds of
6 problems identified earlier there's no ready answer, both
7 at a technical and, I think, legal level, and we really
8 require, I think, a conversation that involves both parts
9 of this debate, the technical and the legal dimension.

10 So, thank you very much, and I hope people will
11 speak with me if they have further questions. Thanks.

12 (Applause.)

13 PANEL 1: ASSESSING THE CURRENT ENVIRONMENT

14 MS. ARMSTRONG: Welcome, everyone. I'm
15 Katherine Armstrong from the Division of Privacy and
16 Identity Protection, and I have to say we've been looking
17 forward to today for a very long time. And so, thank you
18 all very much for coming and welcome to Panel 1.

19 Today we -- this panel is going to examine the
20 current uses of big data in a variety of contexts, from
21 marketing, to credit, to employment, and insurance, and how
22 these uses impact consumers. Today we hope to do one of
23 the things I think the Commission does best, and that's
24 to ask questions, to listen, and to learn. Before I
25 introduce the panel, I want to remind everybody that

1 Solon's PowerPoint or his slides are available on our
2 website and well worth studying, as well as his paper.

3 So, let me briefly introduce our panel, and
4 then we'll begin. Kristin Amerling is the Chief
5 Investigative Counsel and Director of Oversight for the
6 U.S. Senate Committee on Commerce, Science, and
7 Transportation. danah boyd is a Principal Researcher at
8 Microsoft Research and a Research Assistant Professor at
9 New York University. Mallory Duncan is the Senior Vice
10 President and General Counsel at the National Retail
11 Federation. Gene Gsell is Senior Vice President for U.S.
12 Retail and Consumer Packaged Goods at SAS. David Robinson
13 is a Principal at Robinson + Yu. And Joseph Turow is a
14 Professor at the Annenberg School for Communication at
15 the University of Pennsylvania. So, welcome and thank
16 you again for agreeing to participate in this panel.

17 I'm going to start with a question about what
18 is big data. What makes this data unique? Is it the
19 three V's, velocity, variety and volume, or does it have
20 something else to do with the relationship derived from
21 making connections among data sets? And you're all free
22 to speak to that, or whoever wants to jump in first.

23 MS. BOYD: Yes, I'll jump in. I've been -- so,
24 I have a mixed background. I started out as a computer
25 scientist, I retrained as an anthropologist. So, I look

1 at big data from both of those lenses. And we can look
2 at the technical phenomenon, and much of what Solon
3 referred to gets at that, but there's also a social
4 phenomenon, which is, in many ways, tethered to the hopes
5 and dreams and fears and anxieties associated with big
6 data. All right.

7 The possibility that we will get to a perfected
8 idea of statistical knowledge, that this will give us a
9 new form of fact that will allow us to make meaning of
10 the world around us, which, in many ways, obscures the
11 complexity of probabilistic information -- right -- which
12 is a lot of what we're dealing with is probabilistic.
13 The data is imperfect, you know, just like Solon was
14 talking about.

15 And so for this reason, I like to think of big
16 data not simply in its technical sensibilities, but as a
17 socio-technical phenomenon that brings with it a lot of
18 different confusion and chaos. I bring this up because I
19 think it's really important to remember this, especially
20 in light of the conversation we're having today, because
21 a lot of what goes on is the uncertainty, not necessarily
22 the formalistic mechanisms of data mining, data
23 collection, or data analytics.

24 MR. ROBINSON: And if maybe I could just
25 briefly pick up on that, I think one of the things that

1 Solon mentioned that I think is extremely important that
2 was also central to the FTC's Report is that in some of
3 these cases you have data that was gathered for --
4 initially for some purpose that didn't require high
5 fidelity, like slightly making more accurate the list of
6 people that you send out a mailer to. And now, in some
7 instances, some of that data is being used for purposes,
8 like, deciding that certain people are likely to be
9 fraudsters and will not be transacted with by actors in
10 the marketplace.

11 And I think one of the great concerns that the
12 civil rights community has is to make sure that where
13 we're confident -- well, I'll speak only for myself --
14 I'm confident that businesses are going to do things in
15 ways that are optimal from a financial perspective, that
16 if something helps to make something more profitable,
17 that it will happen. But I think, you know, what is the
18 harm from a civil rights perspective versus from a
19 business perspective when the occasional minority or
20 unbanked, or underbanked, or otherwise marginalized
21 person is incorrectly excluded from some product that
22 they'd be ready to transact with. You know, at some
23 level some amount of that is a cost of doing business.
24 And I think one question is whether the amount of that
25 that's acceptable as a cost of doing business is the same

1 or is different than the amount that is acceptable as a
2 civil rights' matter.

3 And I'll just say -- I mean, we -- our group of
4 technologists that works with civil rights folks released
5 on Friday a new report on big data and civil rights,
6 which you can find at bigdata.fairness.io, which does our
7 very best to sort of inventory these concerns.

8 MR. GSELL: So, I'd like to go back for a
9 second to what is big data? Data's been around for a
10 really, really long time. And people have been using it
11 and analyzing it and trying to figure out what it means
12 and what they should do with it.

13 Today, there's just more of it. This phenomena
14 that this new thing called big data has existed, it's not
15 something that just came into vogue; it's something
16 that's been around a long time. And big data, by real
17 definition, is more data than your organization can
18 handle. Okay. I mean, that's big data. So, if you've
19 got more stuff coming to you at home than you can deal
20 with, you have big data.

21 The question really becomes, as more and more
22 data sources become available, more and more data is out
23 there, how do you gather it and make sense of it? I
24 think the -- I think an awful lot of people give the
25 industry more credit for sophistication than actually

1 exists. Most people for the most part are still somewhat
2 overwhelmed and a bit behind the curve on the notion of
3 dealing with all of the new informational data that's
4 coming through.

5 MR. TUROW: Can I just pick up on that? I
6 agree, and I've talked to a lot of people who say exactly
7 what you say in the retail business; for example, that
8 they're overwhelmed and that we're at baby steps now.
9 But it's the beginning of an era. And I would object to
10 the notion that big data are simply the continuation in
11 volume, because when you start adding velocity, and
12 volume, and variety, and the notion then becomes
13 predictive analytics, we're in a different world.

14 We're in a world where hundreds and hundreds of
15 data points are used to come up with conclusions about
16 people that are almost not even intuitive a large part of
17 the time. You come up with the -- you have a key
18 indicator that you're trying to look for, but the notion
19 of which data are going to be used in the end -- an
20 example, which may sound crazy, but I -- you know, it's
21 not totally nuts.

22 Let's say you're a retail establishment, and
23 you're interested in trying to predict which people are
24 going to become less-valued customers, and you have a
25 definition of a less-valued customer. You run your data

1 with your hundreds of thousands of customers and you find
2 that people who start buying vegetable seeds for planting
3 in an urban environment predict that they are going to
4 become less-valued customers in the sense of giving back
5 more stuff, you getting only for sales.

6 Now you might say, what does one have to do
7 with another? I could think -- and this gets back to
8 what danah was saying, there are lots and lots of reasons
9 we could think about, and I could give you some, as to
10 why a person buying vegetable seeds would be predictive
11 as a customer you wouldn't want to deal with the way you
12 deal with other customers, giving discounts and other
13 things like that.

14 But from the big data standpoint, the key is
15 it's predictive, okay. We may not be sure why it's
16 predictive and it gets used like that. And the notion of
17 personalizing data that way is a terrific change in the
18 way companies begin to evaluate their customers on many
19 different levels.

20 MR. DUNCAN: Let me just say a couple words
21 about the retail industry. Obviously, we operate on a
22 very narrow profit margin. It's about two percent on
23 average. And so it's important for the industry that
24 we're able to find those customers who are going to be
25 long, loyal, valuable customers.

1 When we talk about big data, in a sense, we're
2 really talking about an expansion of what's always been
3 done in the retail industry. If you go back a hundred
4 years and you think about how your typical store worked,
5 the store manager was constantly analyzing the shoppers
6 in his store and trying to determine what is it I have to
7 move in the store in order to attract more people; what
8 is it I have to say to this customer in order to increase
9 the loyalty. What big data, or what's referred to as big
10 data, is an expansion of that effort. They are new
11 analytic tools in order to accomplish the same thing. If
12 we're not able to bring people in the store and not able
13 to get them to increase what they're spending, then
14 chances are the store's not going to survive.

15 MS. BOYD: I think this actually raises a
16 different question which is tethered to the topic of
17 today, which is, how do we even start to measure or
18 make sense of fairness? Which is usually where we're
19 starting to think about sort of the challenges of how big
20 data gets used.

21 Now, in the American historical context we usually
22 have a battle between equality and equity as our models
23 of fairness, right? Equality is the idea of equal
24 opportunity, we create that even playing field, everybody
25 enters the table at the same fair starting point, and

1 that's how we constitute fairness is when we have equal
2 opportunity. Equity, of course, is saying, guess what,
3 we have a large amount of systemic issues that result in
4 the fact that people do not enter the table at the same
5 playing field, or same level, so how then do we think
6 about offsetting or dealing with those structural issues
7 and how do we think about reconstituting, you know, the
8 societal infrastructure so we can think about fairness,
9 right? And mind you, we have a long debate in the U.S.
10 on this issue of equity. Right. We get into this
11 discussion of affirmative action. We get into this
12 discussion of whether or not that constitutes socialism,
13 and politics, politics, politics.

14 But there's a third logic that big data brings
15 to bear with what we talk about as fairness. Something
16 that is very much coming from the market-driven logic
17 that Mallory talked about -- right -- which is the idea
18 that we're trying to optimize out efficiencies, and to
19 think about distribution of limited amounts of resources.
20 Think about how we allocate in the best way possible in
21 order to either maximize profit, minimize, you know, law
22 enforcement officers on the street; you know, in another
23 context, thinking about how we distribute resources or
24 maximize opportunities.

25 The challenge with that is that market-

1 driven logic of fairness often really comes up pretty
2 viciously against our notion of what is equity, because
3 of the fact that, as Mallory pointed out, we have these
4 really small margins. And the question, then, is who
5 bears the responsibility for, you know, the fact that we
6 have, you know, retailers who need to figure out how to
7 be profitable? I mean, we have the fact that many, you
8 know, of our customers are not going to be that
9 profitable element.

10 We've had this historically, right? Where do
11 we actually allocate new, you know, stores? Do we do it
12 in a way that is near neighborhoods who are not
13 considered profitable? How, then, do we think about the
14 social ecosystem? The reason I bring this up is because
15 big data is , when used well, when the
16 predictive analytics are done right, when the data mining
17 is done with some level of statistical accuracy, you can
18 get to a point of all of that unintended discriminatory
19 or unfair outcomes because of the fact that we're trying
20 to minimize -- you know, you're trying to maximize
21 profit, minimize, you know, risk, and really deal with
22 those efficiencies. And that's part of the trade-off in
23 a commercial setting.

24 MS. ARMSTRONG: And we're going to be following
25 up and circling back to the fairness and ethics as we

1 continue on with this panel, but I think that's an
2 important issue to bear in mind because it resonates
3 through all that we're talking about.

4 I'd like to ask Kristin to also describe a
5 little bit some of the findings of the Senate's Big Data
6 Report last year.

7 MS. AMERLING: Sure. I'd be glad to, and thank
8 you for the opportunity to participate today.

9 Chairman Rockefeller, as Chair of the Senate
10 Commerce Committee, recently conducted an inquiry into
11 how consumer information is collected, analyzed, shared
12 and sold that I think shares the goal of this panel
13 today, which is assessing what is the current landscape
14 here. And just to give you a little bit of background,
15 the inquiry was conducted by reaching out to nine major
16 data brokers to ask what are their practices in
17 obtaining, analyzing and sharing consumer information.
18 And Chairman Rockefeller released findings in a report at
19 the end of last year, a majority staff report.

20 I think that there are four major findings that
21 are particularly relevant to the discussion that we're
22 having on this panel and today.

23 First, companies, data brokers that collect
24 information without direct interaction with consumers,
25 and often without their knowledge, are collecting a

1 tremendous volume of data and it has tremendous
2 specificity.

3 Second, the companies are collecting this
4 information from a very wide variety of sources.

5 Third, the result of analyzing this information
6 that is collected includes products that are lists of
7 consumers that define them by characteristics that
8 include their financial and health status, including
9 groupings of consumers based on financial vulnerability
10 and other vulnerabilities, and they include another set
11 of products that the Chairwoman referred to this morning
12 relating to scoring consumers, predicting their behaviors
13 based on data that's collected. And some of these
14 products very closely resemble credit scoring tools that
15 are regulated by FCRA raising questions about how these
16 products that may or may not fall under the FCRA are
17 being used.

18 And finally, the fourth finding that I think is
19 worth noting is the lack of transparency that consumers
20 have into data broker practices. And I'm happy to
21 elaborate a little bit more on the four points.

22 MS. ARMSTRONG: Well, you know what, why don't
23 you weave them in as we continue the -- the conversation?

24 MS. AMERLING: Okay. Sure.

25 MS. ARMSTRONG: But raising one of the points

1 that Kristin just brought up, I wanted to also throw out
2 to the group whether where -- whether where the data
3 comes from matters? Whether it's coming from internal
4 sources, external sources, third parties, whether it's
5 passively collected or actively collected? Does it matter
6 in terms of use or types of information?

7 Joe?

8 MR. TUROW: Yeah, I think it matters a lot, but
9 I think we have to be careful to say that just because a
10 store, for example, collects the data, it's not a
11 problem. The example I gave with the seeds -- just to
12 push that a little bit forward -- could reflect a hidden
13 discrimination.

14 Let's say a person begins to plant a garden in
15 her urban area because she's just lost her job, has to
16 take care of her grandchildren. Those kinds of subjects
17 can be brought out, not in direct discrimination, we know
18 this person has lost her job, we know this person had to
19 take care of her grandchildren, she has no husband or
20 whatever, but rather, the fact that she's buying
21 vegetable seeds. You see, it's the idea of hidden
22 discrimination even within a particular store.

23 Now, add to that the things that you can buy
24 from third parties that could build even greater profiles
25 about people without anyone knowing that it takes place.

1 People going through stores with loyalty cards, and then
2 the material gets put on top of that which can lead to
3 many types of discrimination that we have no clue about.

4 MR. GSELL: So, that's certainly a possibility,
5 I mean, the inherent when you do analytics on data, but
6 one of the things that really is driving a lot of the
7 change is the ability to process all of this data. It's
8 one thing to collect it; it's another thing to actually
9 do something with it, okay, and I would contend that the
10 ability to tease out -- actually, to eliminate the need
11 to sample. So, historically, data was so big that you
12 did samples, and inherent in samples are some of the biases
13 because they're based on how the sampler decides to set
14 up their sample set.

15 When you have big data and you have the ability
16 to use what I'll call "big compute against big data," you
17 eliminate the need for sampling. And when you eliminate
18 the need for sampling and you go against the entire data
19 set, you have a much greater chance of eliminating
20 historic bias that have existed based on the way people
21 have decided that this represents an entire population.
22 You don't have to represent an entire population anymore.
23 With big data and big analytics, you can hit the whole
24 thing.

25 MR. TUROW: But that's my point. See, that's

1 exactly what I'm saying. What I'm saying is that
2 increasingly companies -- and now it's harder, five years
3 from now it will be easier -- companies will be able to
4 use data in variety, velocity, and volume in such a way
5 as to personalize a model. So that if I find that there
6 are a thousand characteristics that I can bring together
7 and come up with just a couple that make me decide that I
8 should go after you, that may be a discriminatory
9 decision and you don't even know it, because the -- the
10 data that you're using are so part of the person's life
11 in secondary ways that they discriminate even though it's
12 not said that it's a low-income person or a person of a
13 certain minority group. It just shows up that way.

14 MR. GSELL: I think you'll give us more
15 credibility or ability than actually exists.

16 MR. TUROW: Okay. The last thing I'll say
17 about that is you're right, but what's happening is, what
18 is the trajectory of interest? And if you look at what
19 people in the business are saying, that's where they want
20 to go. They don't say they want to discriminate, but
21 they want to say we want to be able to predict what a
22 person is going to do when that person is walking into a
23 store.

24 Eric Schmidt at one point said about Google, we
25 want you to go to Google to find out what your job should

1 be in the future. Okay. That's what he said several
2 years. We want you to go to Google to find out what your
3 career ought to be. That's quite a statement. They
4 can't do it now.

5 MS. BOYD: So, one of the things that's
6 important to understand is that the data that we're
7 talking about is not just about the data that you may
8 give to a company or a data broker or even your
9 interaction purely with them, but in many ways it's about
10 how you fit within a network of other actors and what
11 else they're doing, right?

12 Historically, we understood this is categories
13 and, in fact, a lot of our conversation about
14 discrimination is a conversation of how one fits into a
15 protected class or a protected category, right? And you
16 think about categories as a way of bucketing. And this
17 had to do with the fact that we didn't have the whole
18 data set and that we couldn't actually imagine the kinds
19 of personalization that we're talking about.

20 Personalization is only made possible because
21 you actually can position somebody in relation
22 statistically through a whole variety of other actors
23 through networks, networks that in many ways are not
24 intentionally designed for by the system creator.
25 They're looking, literally, for correlations that they

1 can see are probabilistic connections. But this also
2 means that we're dealing with data sets, or people, that
3 don't have say over what goes on.

4 So, I think about this, for example, with
5 Facebook, right, which is -- and part of to keep in mind
6 of all of this is all of the businesses have different
7 reasons why they're doing different things, right?
8 Facebook wants to give you a service that if you have not
9 signed up to their site before, they want, when you come
10 in, that you don't end up in this weird desert of no
11 friends, no content, no nothing, right, because that's
12 miserable. And so one of the things that they have
13 gotten much better at doing is determining, before you've
14 even shown up, what is the likelihood that you sit within
15 a particular network?

16 Now, they can do this because of the fact that
17 your friends have most likely updated your email or added
18 your email address to their system, right? So, your
19 friends made decisions to give information about you to
20 Facebook, right? They can do this because they can also
21 assume, once they have that basic information, they can
22 make who else within the network -- what do the people
23 like, what are they interested in, and they can start to
24 say, hey, might you be interested in this, and give you
25 some channel to start engaging.

1 But -- and this is where we get to this
2 question of -- you know, what kinds of data are we
3 talking about? That individual never gave over their
4 information, they didn't give over their list of friends,
5 their friends gave away them and the site was able to
6 interpolate. And this is what becomes part of the
7 challenge of a lot of the data analytics technics that
8 we're talking about. We're not talking about a known
9 trade-off between an individual and a data analyst.
10 We're talking about the way in which an individual is
11 positioned, intentionally or unintentionally, within this
12 network based on what they have or have not given over,
13 or what's been given over about them without their even
14 realization of it.

15 MS. ARMSTRONG: So, let's follow this up a
16 little bit. So, how does it -- does it matter how this
17 data's being used? I mean, danah's been talking about
18 the social network context. I'd like to take it back a
19 little bit to traditional marketing or eligibility-type
20 determinations. Does the use of the data help define how
21 it -- how it should be collected or how it should be
22 used?

23 MR. DUNCAN: Models are at best, as I think it
24 was discussed earlier, just estimates. And we don't know
25 how reliable they're going to be in every instance. And

1 you can imagine -- and they can be accurate or not. You
2 can imagine a company trying to sell a very expensive
3 automobile, and it pulls various lists, and it says
4 there's a 30 percent chance that people will come into
5 your showroom to look at this car versus another list
6 there's a 20 percent chance and five percent. So, they
7 -- they have the money to send out 10,000 solicitations,
8 and they're going to obviously pull from that first list.
9 They might not realize until later that that list is 95
10 percent men and five percent women.

11 Now, is that a fair determination? Is that
12 accurate for that car? Well, if the car happens to be,
13 say, a Maserati Gran Turismo, it may turn out that men
14 are much more interested in a car that is a \$200,000
15 phallic symbol than are women.

16 (Laughter.)

17 MR. DUNCAN: But you can't really say that the
18 -- the use of the analytics was inappropriate in that
19 case.

20 MR. ROBINSON: Can I -- I think one thing that
21 is so important and is sort of not yet part of what we're
22 often talking about, but is sort of under the surface of
23 what we're talking about, is the desire that consumers,
24 and historically, the regulatory regimes have to
25 understand why decisions were reached.

1 So, one of the big things that happens in the
2 Fair Credit Reporting Act (FCRA) context is that if an
3 adverse decision is reached, of course, the consumer has
4 this right to have explained to them why the decision was
5 reached, which means that if new kinds of data are being
6 used to reach FCRA-covered decisions, there needs to be
7 this ability to spell out in some fashion how did that
8 decision arise from that data.

9 And, relatedly, in the Equal Credit Opportunity
10 Act (ECOA) context, a model that has a factor in it that's
11 correlated with protected status, which, of course, many
12 of the key factors are that predict creditworthiness,
13 sadly, because creditworthiness is itself not uniformly
14 distributed across protected status groups and the
15 majority.

16 So, how do you decide whether --
17 notwithstanding the fact that it correlates, say, with
18 race, a factor can still be used in the credit model?
19 And it turns out there's a -- there's a two-factor test.
20 One is that the factor has to have a statistical
21 relationship to creditworthiness, which is unsurprising.
22 And the other -- excuse me -- the other requirement is
23 that the factor has to have an understandable
24 relationship with creditworthiness.

25 So, under existing ECOA precedent, if buying

1 seeds at the store predicts that you are a bad credit
2 risk, and someone wants to use that in a credit model,
3 even if the prediction is stronger than lots of other
4 more intuitively financial-related factors, it may
5 nonetheless turn out that that use is not acceptable
6 because the relationship is not -- in the words of the
7 financial regulatory guidance -- understandable.

8 And I actually think that one -- it's a central
9 tension in big data because when you think about the
10 promise of it, it's to surface relationships that weren't
11 intuitively obvious to us in the first place. Things we
12 didn't already know, but then, nonetheless, are useful in
13 the marketplace. But I think that, you know, to the
14 extent that the payoff from these new technologies is to
15 tell us stuff that we couldn't intuitively have figured
16 out, by the same token -- it's a double-edged sword,
17 right -- by that same logic you have the problem of it
18 being very difficult, potentially, to explain either to
19 consumers or to make visible to regulators what the
20 relationships are, or even for the -- the decision makers
21 in business themselves to understand what are the reasons
22 why certain factors are ending up in these models.

23 MR. GSELL: But there's also a tendency to have
24 big data be more inclusive than exclusive. And I'll give
25 you a quick example. We work with the State of North

1 Carolina and their education system. And one of the
2 things that has been determined to be very important
3 about education and going through education is the
4 ability to take Algebra in the eighth grade. Okay. Now,
5 historically, the way you got into eighth grade Algebra
6 was teacher recommendations. We've been able to work
7 with North Carolina around analytics to analyze test
8 scores, just pure test scores, from the fourth grade
9 through the eighth grade -- through the seventh grade
10 actually, to determine that there is a group of the
11 population that is normally not considered for pre-
12 Algebra, or for eighth grade Algebra based on
13 combinations of things that are beyond just the test
14 scores, or things in the test that are more than just the
15 actual answers.

16 And as a result of this, we've identified -- or
17 the State of North Carolina -- the schools have
18 identified 20 percent more students who were not eligible
19 for eighth grade math based on teacher recommendations.
20 And of those 20 percent more students, 97 percent of them
21 go through eighth grade Algebra without a problem. So,
22 they would have otherwise been excluded, but through big
23 data and analytics they're included and they succeed.
24 And it's a huge win for inclusion, not exclusion.

25 MS. ARMSTRONG: Okay. Let's -- does anyone

1 have some examples of how big data has been inclusive or
2 solved a problem similar to what Gene has laid out in
3 either the traditional credit or marketing/advertising
4 context?

5 So -- all right.

6 (Laughter.)

7 MS. ARMSTRONG: Then let's -- let's take this a
8 slightly different way, but I would like the panelists to
9 be thinking about real examples that they have, because
10 one of the goals of this panel is to sort of lay the
11 landscape of current usage. So, let me --

12 MR. GSELL: I have lots more.

13 MS. ARMSTRONG: Oh, good. Well --

14 MR. GSELL: But I figured I wanted to let other
15 people talk, so I'll just -- I'll hold them and work them
16 in.

17 MS. ARMSTRONG: How about -- why don't -- you
18 can -- how about why don't you do another one and then
19 we'll see if that triggers.

20 MR. GSELL: All right. So, along the lines of
21 credit scores and how people are included or excluded,
22 through the use of better data and better analytics, one
23 of the large auto companies that issues credit on a
24 regular basis has been able -- and, historically, they're
25 very conservative, okay, which is we want our risk

1 profile against our consumer loan base to look like this.
2 They've been able to use big data to actually include
3 more people in the sample set than exclude. So, they
4 actually have a mantra, which is how can we be more
5 exclusive, turn down less people if you will, okay, so
6 that we can tease out the people who historically don't
7 have a good FICO score but they are in fact still good
8 credit risks. Okay.

9 So, working with them and through the analytics
10 we're able to find the people who are normally excluded,
11 include them back into the population to give credit to.
12 And, again, the historic default rate on the incremental
13 people that we bring back into the population is lower
14 than the historic credit failure rate across the entire
15 data set.

16 MS. ARMSTRONG: So, I think that weaves into
17 one of the comments that David's paper that was released
18 earlier -- or last week -- noted that 70 million
19 consumers do not have credit scores. And that
20 alternative data can often be a positive way to include
21 people that previously aren't part of that mix. So,
22 Gene, without going into the special sauce, can -- can
23 you tell us what kind -- what is it about the scoring and
24 analytics of credit that allows non-traditional data to
25 be used in such a positive way?

1 MR. GSELL: So, I'm not a credit expert.

2 MS. ARMSTRONG: Okay.

3 MR. GSELL: I will preface by telling you that.
4 There's an ability to get more sophisticated modeling
5 across a larger data set. And the more information I
6 have -- it's a classic statistical problem -- the more
7 information I have, from a statistical forecasting
8 perspective, the better able I am to predict. So, by
9 bringing in more data, different vehicles, different data
10 vehicles, I'm able to, if you will, tease out, okay, the
11 most likely to be successful credit worthy people. Okay,
12 but I can't tell you what the algorithm does.

13 MS. ARMSTRONG: Okay. All right.

14 MR. ROBINSON: I mean, so, just to go
15 specifically to sort of additional data and credit
16 worthiness, I mean the big sort of frontier there that
17 has been -- that has shown signs of statistical strength
18 has to do with the payment of utility bills, so cell
19 phone bills, power bills, things like that. And, you
20 know, on the one hand there may be people for whom
21 traditional, you know, FICO score data does not exist,
22 nonetheless, they've been paying their power bill on time
23 for many years. Turns out that's a good predictor that
24 they would be a good loan risk. And so, by including
25 that data there is the potential to expand the group of

1 borrowers for whom the lender can have confidence that
2 they are likely to repay.

3 Nonetheless, when you change how data is used
4 from one purpose to another purpose there are also social
5 justice risks. So, in this context, for example, with
6 utility payments in New England there are many states
7 that have assistance programs where if you are unable to
8 pay your power bill they will keep your heat on in the
9 winter, but what they require you to do is show that
10 you're delinquent in the payment of your power bill in
11 order to receive the needed assistance. They say you
12 don't have to skimp on food, you can buy your groceries
13 and not pay your power bill and then we'll come in and
14 help you. Of course, if the world changes in such a way
15 that that power bill now becomes also the key to
16 accessing credit, then that conflicts with that
17 assistance program in a way that may lead those people to
18 have, you know, a really difficult choice where the state
19 assistance program ends up, in effect, saying that you
20 have to commit some kind of like, you know, credit self-
21 harm in order to keep on getting help keeping the heat on
22 in the winter.

23 Now, of course, the possibility exists to
24 revise, you know, those programs in ways that resolve
25 that concern. But I guess what I'm really saying is that

1 the -- the benefits that are there, I think, are best
2 realized when we tread particularly carefully with the
3 repurposing of data that was gathered in one context, you
4 know, for use in another. And I would again say the use
5 of data to lock people out of transactions that was at
6 first gathered for market purposes where errors were much
7 less of a concern is a serious social justice concern.

8 MS. BOYD: So, you'll notice that one of the
9 things that happens is that we're often going to public
10 sector examples. And part of the reason why we do this,
11 even as corporates are working with public sector, is the
12 fact that many of the decisions that are made within
13 private enterprises are not visible. And so, this
14 becomes a trade-off, right. Do you assume that the
15 private sector actors are inherently evil, or do you
16 assume that they're actually trying to do the right
17 thing? And, right, we can agree or disagree on a whole
18 variety of that.

19 And I think that's actually where it becomes
20 really difficult, because these same technics that can be
21 used to increase different aspects of fairness can also
22 be used to create new kinds of complexities. And it's
23 that tension that becomes really difficult because it's
24 often not visible. And it's not only just not visible to
25 outsiders, it's often not visible to the actors

1 themselves as they're trying to do a lot of the
2 predictive analytics that they're working on. Right.
3 We're working with complex learning algorithms. Do the
4 engineers even understand what's going on? And this is
5 where we get back to this question of scoring as an
6 example there.

7 Now, the other thing is that when you do this
8 kind of work, what do you do as the intervention? Right.
9 So, I'll give an example. So, in Microsoft Research,
10 which is the academic arm of Microsoft, which is nice
11 because it means researchers publish a lot of their
12 experiments. And so, you can see certain attempts to try
13 to figure these things out. And I'll give an example
14 from a non-focus on discrimination, but it shows the
15 challenge here.

16 Eric Horvitz is a researcher at Microsoft
17 Research and he's at the point with Bing data where he
18 can predict with a high level of probability, depending
19 on somebody's searches, whether or not they're going to
20 be hospitalized within the next 48 hours. Right. That's
21 a really interesting puzzle. Now, the question is, what
22 do you do with that information? Right.

23 If you are Microsoft and you are running Bing,
24 does that mean you send a warning sign, like, you're
25 about to be hospitalized. Like, that's creepy, right.

1 Like, what's going on with that? Does that mean you
2 figure out, you know, a subtler way, a slight
3 advertisement, as a way of suggesting that they might
4 think about it? Again, where do we get on the sort of,
5 you know, Minority Report creepy zone of it all? Or do
6 you not do anything because you don't want to, you know,
7 deal with the liability? Those are ethical questions
8 that become part of it. Things that companies struggle
9 with all the time when they're doing this. Right. They
10 start to see a trend, they start to realize a
11 correlation, and they go, okay, how do we intervene in an
12 appropriate way?

13 Now, of course, this also becomes a challenge
14 when companies have to think about the responsibility
15 they have beyond their particular domain. So, for
16 example, JP Morgan and Chase does amazing analytics work
17 to predict with high levels of probability whether or not
18 somebody is engaged in trafficking of humans,
19 particularly for sex. Right. And they can do this based
20 on a whole set of different financial patterns that
21 become obvious. Okay. So, their response, because, you
22 know, their company, they don't know how to intervene in
23 human trafficking, right, why should they? So, of
24 course, they're going to work with law enforcement. But
25 that sometimes is a good idea and sometimes not. Right.

1 And a lot of people who work on trafficking issues have
2 identified why often law enforcement is not the best
3 intervention point where social services is. So, how
4 then do we think about the ethics of those responses?

5 And this is where we've got this big challenge
6 with corporations. What are they choosing to look at?
7 Are they choosing to do it in a way that we deem to be
8 ethical or appropriate? How do -- what do they do with
9 the information that they get? And when and where do
10 they, or should they make this information public?

11 And it's not easy to work things out. So, I
12 don't want to assume that just our silence and failure to
13 give examples is not that companies are engaging always
14 in bad -- you know actressing. A lot of is that these
15 things aren't visible for a whole variety of complex
16 ethical concerns.

17 MS. ARMSTRONG: And I think that's one of the
18 points of Kristin's that the report showed last year.
19 Would you care to elaborate on that?

20 MS. AMERLING: Yes. We ran into this lack of
21 visibility issue in a number of ways when were looking at
22 the practices of the representative data broker
23 companies. First, the companies are gathering
24 information largely without consumer -- direct
25 interaction with the consumer, so the consumers

1 themselves aren't really aware that the companies are
2 using their information or that the companies necessarily
3 even exist. And then, in looking at the contractual
4 provisions provided to the committee, we saw that that
5 many of the companies perpetuate this secrecy by
6 including contractual provisions in their contracts with
7 their customers that say you're prohibited from
8 disclosing what your data source was.

9 And then, even when a number of companies do
10 provide -- a number of the companies we surveyed do
11 provide some rights of access for consumers to look at
12 the data that they have on them. And in some cases they
13 provide some rights of correction if the consumer feels
14 the data is inaccurate. But even when those rights are
15 provided, and not all companies do provide them, they
16 don't have much value when the majority of consumers
17 aren't even aware that the companies exist or are
18 collecting this data.

19 And then, we, in addition, ran into several
20 large companies that outright refused to provide to the
21 committee who were their specific data sources and who
22 are their specific customers. So, those were all
23 obstacles to trying to understand, you know, how the --
24 how this information is being used and analyzed.

25 MR. DUNCAN: Companies are in a very

1 interesting situation right now, especially in the retail
2 community, because we're in a transitional period. For a
3 long time in the world there existed the online
4 community, which a great deal of information tends to be
5 gathered. And then, there's the in-store community where
6 it's a lot more -- a lot more meager. And we've seen a
7 behavioral in stores and in consumers where they want to
8 view this as omnichannel. And they want to buy it
9 online, and they want to return it in the store. Well
10 that means there has to be data flows back and forth
11 between those two -- those two markets. And so, the
12 folks who are running the store have to figure out how
13 far can we go?

14 And what we find happens -- and this may
15 explain some of the information shortages that you're
16 talking about -- what happens is that they look at
17 correlates to what consumers expect in terms of the use
18 of information in the store, and that's the model they
19 use. So, they tend to be very conservative in terms of
20 expanding the use of the data or the expansion of that
21 data in a store market.

22 MS. ARMSTRONG: Can you give an example of
23 that?

24 MR. DUNCAN: There is -- there is what -- there
25 may be cookies that are used online that will travel from

1 location to location. In a store environment we're
2 uncomfortable with that kind of movement. We would say
3 consumers are comfortable being observed in the store,
4 and so information may be gathered and used within the
5 store context. But they're very reluctant to go beyond
6 that because that violates consumer's reasonable -- or
7 the -- that violates the store's expectation as the
8 consumer's reasonable expectation.

9 MS. BOYD: Let's be clear that Mallory's
10 hinting at the fact that there are actually a lot of
11 startups out there that are actually trying to track
12 mobile phones into stores. And there's a big tension
13 within the retailers as to whether or not to implement
14 that because it parallels the cookies issue. It allows
15 you to literally track a unique identifier of a phone,
16 see whether you've seen that person before, see what
17 their patterns are, see how they're navigating the store,
18 all of that is technically feasible, the question is
19 whether or not retailers want to implement it or what the
20 challenges are of doing so.

21 MS. ARMSTRONG: I think Joe wants to add
22 something.

23 MR. TUROW: Well, I've spoken to a couple
24 people who say they do exactly that now. And all you
25 have to do is think about loyalty cards. Loyalty cards,

1 which are kept by virtually everyone here who goes to a
2 supermarket, probably uses a loyalty card, it's like 90
3 percent of Americans who go to supermarkets that give out
4 loyalty cards use them, because otherwise you lose a lot
5 of money if you don't. They track everything you do.
6 Until the last few years they haven't been able to much
7 with it, they haven't, for lots of reasons, done any big
8 data analysis, and that's changing totally. Okay. And
9 there are companies, for example, Kroger owns part of
10 Dunnhumby, which is a company that is designed just to do
11 these sort of analytics. The idea now -- companies like
12 Macy's and others are putting pods of these beacons in
13 stores that look at you when you reach you a certain
14 point and then give you specific blandishments, like,
15 discounts based upon your shopping habits. Catalina
16 Marketing for decades have been giving people these long
17 coupons as you check out, based upon 52 weeks of looking
18 at your shopping habits anonymously. Now they're
19 beginning to do stuff in the store in a digital sense and
20 outside the store.

21 So, we -- in fact, you're absolutely right
22 what's happening now is stores are getting so nervous
23 about the online environment that physical stores are
24 bringing the internet to the store. And the big data are
25 extremely a part of that in ways that danah mentioned and

1 in other ways as well. And it's a -- that's exactly
2 what's happening. It's a fascinating trajectory partly
3 because of the growth of big data in the online world.

4 MR. DUNCAN: And, if I could, it's also because
5 the consumer expects that seamless experience. And it
6 presents the retailer with a bit of a dilemma. You want
7 to treat the consumers in the way they want -- like to be
8 treated, but you want to be sensitive to the privacy
9 implications and the use of the data at the same time.
10 And how you square that circle depends on the reputation
11 of each retailer.

12 MS. ARMSTRONG: But is it a transparency issue?
13 I mean, do you think we're at a -- that in five, ten
14 years it will be totally different because the consumer's
15 expectation of privacy or not sort of being their
16 purchases or their behavior being followed? I mean, I
17 almost hear you saying that it's sort of expected online
18 but not in a store. That seems like a little bit of a
19 disconnect to me.

20 MR. GSELL: Well, to some extent, it's
21 generational.

22 MS. ARMSTRONG: Uh-huh.

23 MR. GSELL: So, I mean, I am high on the creep
24 factor --

25 MS. ARMSTRONG: I was going to say, you and me

1 are the same generation.

2 MR. GSELL: -- on some of those particular
3 things. Yeah, but my kids, you know, they have no
4 problem.

5 MS. ARMSTRONG: Right.

6 MR. GSELL: They expect that to your point.
7 They expect the same kind of offers and service and
8 interaction online when they walk through the store they
9 expect the same experience.

10 MS. BOYD: Now, I think I'd be -- I want to
11 sort of butt in there, because young people -- there's a
12 lot of self delusion. Young people are actually just as
13 self deluded about a lot of this as we adults are. Like,
14 there's not this big difference between young people.
15 They want privacy, too. They're focused very heavily on
16 the people who hold immediate power over them.

17 I want to just think through an experience all
18 of us had. Right. We came in here this morning, in some
19 ways we knew it was going to be recorded, we knew people
20 we're going to take pictures, we're at a public event,
21 right. You saw the webcast notice. And yet, when we
22 heard this morning the listed detail of, like, if, you
23 know, if you object at any moment to a photograph being
24 taken, you know, as Tiffany went through this you're
25 sitting here going, "I want to leave," right, like, "This

1 is really creepy." Right. And even though you know it
2 part of it is that you had put it down, you had avoided
3 it, you hadn't thought about your hair in perfect, you
4 know, coiffed form.

5 This is one of the challenges that we run into
6 all of the time, which is that notice and information is
7 not always the best way to actually create a meaningful
8 relationship. And there's a lot of self delusion on both
9 sides. The reality we also -- we collect a lot of
10 videotape that we never look at. Right. My guess is
11 that most of us are never going to look at the videotape
12 of how badly our hair looks on that camera. Right. Part
13 of it is this interesting challenge of how much do we
14 purposefully sort of put this information aside and
15 navigate it through.

16 But I would not put this as a generational
17 issue. This is not a generational issue. And Chris
18 Hoofnogel, in particular, has done phenomenal work
19 looking at the consumer side of it. Young people feel
20 the same way as adults, their trade-offs look different.

21 MS. ARMSTRONG: But is it an educational issue,
22 then? I mean, it's easy to suggest that it could be a
23 generational thing or not, but I -- I wonder how do we
24 educate people, not just adults, not just children or
25 younger people, to expect that or to know that their

1 transactions will be recorded or collected.

2 MS. BOYD: But you're basically asking to
3 educate them about the fact that they are powerless.
4 Right. Like, that's what the education ends up being
5 about. Like, either you opt out of this room, right, or
6 you'll be recorded. Period. You have no say. And
7 that's one of the trade-offs that happens all the time
8 online, or in these -- you know, commercial environments.
9 Right. You want to go and buy something from Best Buy,
10 you will be recorded, get over it. Right. Otherwise,
11 don't go into Best Buy.

12 MR. ROBINSON: And just to pick up on this
13 transparency and on something that danah earlier said
14 about how, you know, we go to these public sectors
15 examples because we don't know what's going on inside of
16 these private enterprises. I think that's absolutely
17 true and is central, really, to the FTC's future
18 decisions about what to do in this area, is that, you
19 know, what -- education about the fact that a practice
20 happens in general does really little, if any, help to
21 try and figure out whether that practice manifests in a
22 discriminatory fashion for particular people.

23 And Dr. Sweeney's work on the discriminatory
24 delivery of online ads is indeed an unique example
25 available in the public discussion, which is why the

1 Chairwoman mentioned it this morning and we've come back
2 to it here. And I think what I'd like to see is a world
3 in which you don't have to be a -- you know, a world
4 leading data scientist, who also happens to personally be
5 the victim of discrimination, in order to have the tools
6 that are necessary to check that that's happening and
7 address it. And certainly after the study came out,
8 Google changed its practices with respect to the delivery
9 ads opposite names in general in order to avoid the
10 discrimination harm of these disparaging arrest-
11 suggestive ads.

12 But that's an extremely unusual case and I --
13 and I think we would all like to see a world in which if
14 harms like that are happening to people who, you know,
15 are not academics and data scientists with kind of all of
16 the resources that it would take to be a personal, you
17 know, sort of scholar of that discriminatory harm, you
18 know, when that harm befalls someone who's in a different
19 position, who's more in a marginalized position, I think
20 what we would all like to see is for those harms to be
21 treated with equal seriousness. But I think the fear
22 that the community has right now, which I think is an
23 extremely well-grounded one, is that when harms of that
24 sort do befall someone who's in a marginalized position,
25 they really don't have the tools today to -- not only to

1 solve, even necessarily, to diagnose those problems.

2 MR. DUNCAN: It's not --

3 MS. ARMSTRONG: But some -- sorry, I was going
4 to say that some would argue that the Fair Credit
5 Reporting Act is a -- is a mechanism in the credit
6 context, because it's doing exactly the sorts of things
7 you're talking about which is when adverse action -- if
8 you fall within, an adverse action is taken, you're
9 provided a notice that the adverse action was a result of
10 something in the credit report, and you're given the
11 opportunity to dispute that information. So, I wonder
12 whether the expectation in the credit world is a little
13 bit different because they know they have this mechanism
14 in place, and whether that's a metric that's useful in
15 another context?

16 MR. DUNCAN: I think we have to make
17 qualitative differences. When we're talking about
18 credit, or insurance, or education, we may have very
19 different expectations than when we're talking about
20 marketing.

21 Let me go back a moment ago to the example of
22 the sports car. One solution would be to say, no, you
23 must send the offer to come in and test drive the car to
24 more people. Well, the consequences to that is that
25 people receive the offer who have no interest in, thus

1 depleting the funds that the dealership has for sending
2 it out, or people will rush in to test drive it who have
3 no ability to purchase the car, thus tying up the service
4 folks at the auto dealership.

5 So, you really have to look at the quality of
6 what you're doing as opposed to just saying let's take
7 the credit reporting structure and apply that more
8 broadly.

9 MS. BOYD: Also, I don't want to dismiss the
10 credit reporting. I think it's an important
11 intervention, and I think -- you know, I'm very excited
12 to see that being a regulatory intervention. But also,
13 let's be realistic. Many of the people that are most hit
14 by it have not the time, not the connections, not the
15 understanding, not the literacy, not the wherewithal, and
16 they don't feel a sense of power to be able to actually
17 fight it in many cases.

18 And so, when we actually look at that, it's
19 also this question of who has all of those resources,
20 those soft resources, to be able to do the thing that
21 they were supposedly protected, you know, for. And
22 that's where this interesting tension emerges of where
23 are we trying to get marginalized voices, whether we're
24 talking about youth, whether we're talking about
25 protected classes, to raise up and try to be powerful

1 against systems of power that are meant to actually
2 challenge them? Or where are we trying to think about
3 the role of different kinds of advocacy groups or
4 different kind of actors who work on their behalf? And I
5 think we have to be realistic about how we're dealing
6 with this.

7 This is the challenge with education. I think
8 a lot of our education narratives go back to consumers
9 without actually thinking about the lack of other
10 resources that they have to make sense of, or feel agency
11 or power in light of what's going on. And I think that's
12 a difference between how we think about it theoretically
13 and what we think about in a regulatory context, versus
14 what I see on the ground, when I deal with a lot of
15 marginalized people who are just like, I don't feel like
16 I have any sense of power to do anything about this so
17 don't tell me about it.

18 MS. ARMSTRONG: So, what's the solution? What
19 are your recommendations for empowering those people?

20 MS. BOYD: I mean, this is where I do believe
21 -- I believe strongly in the role of advocacy as a
22 mechanism to be speaking on behalf of groups. And this
23 is one of the reasons, you know, Dave and I spend a lot
24 of time talking with different legacy civil rights groups
25 for this reason. Like, those folks need to be educated,

1 you know, on behalf of populations as opposed to -- and
2 they need to have the transparency and the tools and the
3 mechanisms with which to hold, you know, systems of power
4 accountable without always going direct to the consumer
5 as the right direction there.

6 MR. ROBINSON: I mean, so, I mean, these are
7 groups that have unique -- you know, that hold the
8 franchise through their -- and have earned the franchise
9 to speak for these communities and policy settings.
10 Right. There are people who -- whose job that is. There
11 are people who do it for, you know, down to migrant farm
12 workers, and really the most marginalized, you know,
13 people, you know, in our country have, you know, people
14 who are there.

15 But I think making the practices transparent
16 enough to give handholds to advocates in those cases in
17 which there's a role that they do need to play I think is
18 a role that FTC itself has often successfully played.
19 And certainly, I think the FCRA is, you know, a good
20 model for the things that it applies to and has certainly
21 -- has played a role in making underwriting a relatively
22 conservative area in terms of the applications of big
23 data as compared to these unregulated, you know,
24 marketing practices.

25 Although, as the Chairwoman noted in the case

1 of these thinly aggregated scores that may be used to
2 lower credit limit that are putatively outside of FCRA, I
3 think it becomes difficult. And frankly, I think there
4 are, you know, legislative and ultimately constitutional
5 questions about how far the FCRA-style model could be
6 extended into the marketing world that I think really do
7 force us to -- and I also -- let's -- you know, law and
8 regulation have a valuable role to play, but so does --
9 but so does corporate citizenship potentially. I mean, I
10 think people who say, you know, we're doing stuff in a
11 way that we would like to be responsible and we would
12 like to take affirmative steps to make sure that we're
13 not inadvertently having disproportionate adverse, you
14 know, impacts, I think there's a role actually there for
15 collaboration with advocates. Because right now it's
16 clear what the sign posts are, what the benchmarks are
17 for making sure that you're not doing these things
18 inadvertently. And I think that if I were to project
19 forward five or ten years, my recommendation, my hope,
20 and also my prediction, would be that there are going to
21 be some practices that emerge, and my guess is that they
22 are going to emerge probably in a collaborative fashion
23 that's probably outside of the legislative process.

24 MR. DUNCAN: David, I want to be very careful I
25 think here, because access to credit is essentially a

1 fundamental right in this country. Access to a high-end
2 men's fashion catalog is not. And we ought not to
3 conflate the two in this discussion.

4 MS. AMERLING: But the --

5 MS. ARMSTRONG: Well -- go ahead, Kristin.

6 MS. AMERLING: I mean, the -- the kinds of
7 products that we saw in our review of data broker
8 practices that involve marketing did go beyond products
9 designed to promote the most appropriate car or reach the
10 people who are most interested in cooking magazines. I
11 mean, there are a wide variety of groupings of consumers
12 based on their financial and house status that includes
13 lists of people who have diabetes, Alzheimer's, or
14 suffering from depression that consumers may not be as
15 happy to find that they're on as finding out that they
16 can be targeted for the best car that's most tailored to
17 their needs.

18 And there was actually an interesting article
19 that just came out last week by Bloomberg on widespread
20 sale of health ailments list that goes right to this
21 point where they reported that just with simple Google
22 searches the reporters were able to find lists of
23 consumers with their names and addresses that were
24 identified as associated with specific diseases. And
25 they interviewed some of these consumers, and one who was

1 associated with diabetes was surprised and not at all
2 happy to find out that he was on this list, and said he
3 didn't have diabetes and nobody in his family had it.

4 So, there are some sensitivities raised by some
5 of these products that I think are a little more in the
6 grey area than just these are the best products to tailor
7 to the needs.

8 MS. ARMSTRONG: So, we're about to run out of
9 time, but I'd like to give everybody on the panel an
10 opportunity to say some parting remarks. We have some
11 question cards from the audience that raise some issues
12 that I think would be worth mentioning. And that is the
13 level of trust that may appear to be missing in the big
14 data context of the relationship of marketers, a person
15 that goes to a store may choose to go to the store, there
16 may be a level of trust there, but the invisibility of
17 big data disperses that trust a little bit perhaps.

18 But I would -- I would like each of you -- and
19 I feel terrible in a way because we have ended this panel
20 talking about what the last panel is going to be talking
21 about more, which is sort of the path forward. So, as
22 you provide your final little remarks, if you would also
23 remember that we were laying the landscape and if you
24 could bring it back to what's happening now as we wrap
25 up, that would be fabulous.

1 MR. TUROW: Okay, I -- I had a path forward,
2 but I'll try to make it a now.

3 MS. ARMSTRONG: As long as you bring it back to
4 the landscape.

5 MR. TUROW: The now part of it reminds me about
6 the -- I think it's shameful that in a commerce committee
7 hearing when a senator asks a representative of the data
8 industry whether he could name his clients, he refuses to
9 do that. These are areas of life that impact all of us.
10 And the collection of information about us and their use,
11 I think should be required -- I think companies should be
12 required to say which data broker -- the data broker
13 should be required to say what -- who they get it from,
14 what are the categories, because these affect us
15 everyday.

16 In terms of education, I think most people are
17 learning about credit cards and loyalty from Jennifer
18 Garner on tv commercials then they learn from anywhere
19 else. We have no learning about this stuff anywhere.
20 People are -- it's totally obscure. And I would suggest
21 that's purposeful.

22 I think the idea of big data is a continuity.
23 There's an element of continuity between that and the
24 quantification of the individual that has gone back 30,
25 40 years. But we're in a century now that I think will

1 be looked at as the century of data, the century of
2 pinning numbers on people and trying to figure out where
3 that leads people. And we're only at the beginning. So,
4 I think we have to realize that this stuff is important,
5 not just for now, and it's going to get much stronger
6 with greater processing and the kinds of things that
7 people are saying today, "we can't do it," are going to
8 be done.

9 So, the issue is not, you know, is this going
10 to happen because it's too futuristic, but when it
11 happens are we going to have the conceptual tools to deal
12 with it.

13 MR. ROBINSON: I just -- to sort of pick up on
14 the question about trust and where things are today, I
15 think there's an unrealized opportunity to create greater
16 trust with consumers in terms of how these technologies
17 are being used. And I think that the tools that we have
18 from prior regimes about notice that your data is being
19 collected -- the notice and content regime, frankly, I
20 don't think offer the tools to create that greater trust.
21 Because, as danah was saying, the data is collected in a
22 way that you don't have fine-grained awareness, and you
23 certainly don't have fine-grained choice about what's
24 going to happen.

25 And I think that the tools that we need in

1 order to be able to have practices happen that -- that
2 gain the predictive payoff from these analytics, but at
3 the same time give consumers good reason to trust that
4 things are being done in a way that they can feel
5 comfortable about, I think those tools have really not
6 been perfected yet, and that we're in a place -- we're in
7 an exploratory initial place now of needing to build new
8 tools for accountability and trust consistent with the
9 business leveraging of these -- of these tools.

10 MR. GSELL: I guess what I'd say is the genie's
11 out of the bottle. Stuffing it back in is not going to
12 happen. Data is a part of what's going on. There's more
13 of it than there ever was, and there will continue to be
14 more than there was last year or this year.

15 I think that, for the most part, the uses of it
16 are much more positive than negative. There are enormous
17 examples of big data being applied to solve big problems,
18 big worldly problems, big human problems, and healthcare,
19 and in genetics and in disease control, in commerce in
20 terms of how to minimize fuel consumption across airlines
21 or UPS, or people like that. For the most part, it's
22 really very, very positive that we can now compute on
23 data that wasn't even available two, three, five, ten
24 years ago.

25 From a consumer perspective, again, I think the

1 economic model still will drive most of the thought
2 process around this. A retailer doesn't want to do
3 something that creeps you out. Okay. And the minute
4 they cross the line they get what is the worst thing
5 possible for them, which is you opt out. And the worst
6 thing for a retailer is a fair amount of opt outs. They
7 want to keep you in the fold. They want to be relevant
8 to you. They want you to be responsive. And their only
9 notion is to give you something more relevant to you so
10 you don't have to filter out all of the noise that's out
11 there.

12 I think that there are clearly some privacy
13 things that need to be monitored and watched, but on
14 balance I think most consumers are electing to opt in as
15 opposed to opt out.

16 MR. DUNCAN: I think Gene said it well. I
17 mean, there are a lot of retailers out there, several
18 million. And so, there's a lot of choice and opportunity
19 for consumers. And trust, in that context, is more than
20 just one element, such as sharing this data flow or
21 another, it really is about developing loyalty with the
22 customer so the customer trusts the retailer and wants to
23 return and maintain that loyalty.

24 One easy example. There are companies out
25 there that gather -- like, Amazon -- gather huge amounts

1 of data, and yet, consumers know this because they see
2 the sign that says if you like this item, you may like
3 that item. They appreciate that, and they go back and
4 shop again and again, because they trust Amazon to do
5 what's right by them. And that's what other stores are
6 aiming for.

7 MS. BOYD: My perspective of this space is
8 actually extraordinary complex, and it's not that they're
9 not inherently good actors and evil actors, it's the fact
10 that everything has a lot of grey zone. You know, the
11 other thing I think is important to highlight in this is
12 that we often talk about companies that we're thinking
13 about as high-level brands. Brands that we can hold
14 accountable and recognize. But then we also deal with
15 data brokers whose names nobody recognizes who are
16 holding on to data, who are buying data at bankruptcy
17 situations, who are capturing things that -- you know,
18 and pulling together data sources that we don't even know
19 about. And this is one of the reasons why this space
20 gets very murky because we often talk about it within
21 specific silos rather than the complexity of it.

22 Anne Washington's been talking a lot about data
23 supply chains, which I think is a way of interestingly
24 thinking about it. It's a metaphor. It's not a perfect
25 metaphor, but it's a really interesting metaphor to start

1 thinking about that. How do we start thinking about
2 holding supply chains accountable when we're thinking
3 about these data issues? Not just in terms of the data
4 brokers that the FTC is looking at, but in terms of all
5 our own acts -- our own behaviors around this.

6 The other thing I think is really important to
7 highlight is that many of the companies, especially the
8 big names, are really trying to do their best. Right.
9 They're trying to figure out how to hold this stuff in a
10 responsible way. But as, you know, David's point out,
11 they don't always know what the best practices should be.
12 And this is where there's tremendous opportunity for
13 meaningful cross-sector collaboration to try to figure
14 these things out.

15 Regulation is one approach. It's a very power
16 strong-armed approach, but collaboration is another
17 approach to start thinking about how do we evolve the
18 best practices and how do they differ per sector, because
19 as Mallory pointed out it's different when we're talking
20 about retailers than versus what we're talking about in
21 terms of finance and credit. What does it look like and
22 how do we pull things together?

23 Finally, I want to sort of end with a
24 philosophical point, which I think is also about the
25 state of being. The notion of a fact in a legal sense

1 emerged in the 1890s. It's a really modern concept. And
2 anybody who lived through the last election in this
3 country saw that we're kind of in post-fact state.

4 (Laughter.)

5 MS. BOYD: For better or worse, one of the
6 things that's sort of coming up as a new equivalent of
7 fact is rethinking probabilistic understandings. This is
8 the big data element. This stuff is here to stay. Part
9 of it is understanding what probabilistic systems mean
10 for our whole ecosystem, because part -- in understanding
11 probabilistic systems you realize it's not cleanly fact,
12 it's about trying to figure out how to deal with this,
13 and how do you hold probabilistic systems accountable,
14 and how do you think about their role in things like rule
15 of law is going to be very, very messy. And this is
16 where I say this because a lot of what we're dealing with
17 in terms of the systems that we're trying to hold
18 accountable are probabilistic systems, which are not
19 intended or designed to be discriminatory in a
20 traditional sense in the narrative of a fact, but they're
21 done in this way that ends up unintentionally doing so.
22 And that goes back to Solon's comment. And I think it's
23 really important to understand that philosophically,
24 because that's one of the things that we need broad-
25 spread literacy on before we run into the systems where

1 we just assume to treat these things as facts.

2 MS. AMERLING: I just want to go back to the
3 issue of transparency and visibility. That's a theme
4 that emerged from inquiry; it's emerged in many of the
5 comments today. The Chairman has proposed legislation to
6 provide consumers access the right to correct their
7 records, the right to opt out if they don't want their
8 information being used for marketing, and this is kind of
9 a baseline for transparency and it's very interesting to
10 hear about these additional non-legislative tools. We
11 recognize this is a complex and evolving issue and are
12 looking forward to continuing to being part of the
13 dialogue about the impact of big data on consumers.

14 MS. ARMSTRONG: Well, I wanted to -- I want to
15 thank everybody for participating in this panel and
16 bringing the different perspectives that you have. I
17 think one thing that seems fairly clear is that there is
18 no single solution or there's not even any single way to
19 look at this. That it's very much something that we must
20 look at through a multi-faceted lens when we're talking
21 about marketing, credit, social media, and all these
22 other topics.

23 I hope we we're a little successful in laying
24 -- assessing the current environment, but I know that the
25 panelists here could have actually participated on any of

1 the panels today because it all does, as danah said, a
2 lot of grey areas. So, thank you very much everyone.

3 (Applause.)

4 MS. ARMSTRONG: And you need to return --
5 audience members, you need to return here at 11:00. You
6 have about a ten minute break. There is a cafeteria, but
7 you can't bring any food in here, so...

8 (Laughter.)

9 (Whereupon, a brief recess was taken.)

10 PANEL 2: WHAT'S ON THE HORIZON WITH BIG DATA?

11 MS. GEORGE: Hello, welcome back. We're going
12 to get started in a couple of minutes. Will the
13 panelists on the second panel please come up to the
14 stand? Please take your seats.

15 (Brief pause.)

16 MS. GEORGE: Good morning again. For those of
17 you who may have missed the beginning, my name is Tiffany
18 George, and I am an attorney in the Division of Privacy
19 and Identity Protection here in the FTC. And welcome to
20 our second panel. We're going to discuss what's on the
21 horizon with big data. As you can see, the first panel
22 touched on a lot of different issues, some of which will
23 be covered in our subsequent panels. But for this panel,
24 we want to focus on potential future trends in big data
25 practices and implications for consumers and

1 organizations.

2 I'd like to thank our esteemed panelists for
3 joining us today. I will briefly introduce them and then
4 we'll dive right into the discussion.

5 Joining us today are Alessandro Acquisti,
6 Associate Professor of Information Systems and Public
7 Policy at the Heinz College of Carnegie Mellon University
8 and Co-director of the CMU Center for Behavioral Decision
9 Research; Pamela Dixon, founder and Executive Director of
10 the World Privacy Forum; Cynthia Dwork, distinguished
11 scientist from Microsoft Research; Mark MacCarthy, Vice
12 President for Public Policy of the Software Information
13 Industry Association; Stuart Pratt, President and CEO of
14 the Consumer Data Industry Association; and Nicol Turner-
15 Lee, Vice President and Chief Research and Policy Officer
16 for the Minority Media and Telecommunications Council.

17 Welcome and thank you again for joining us.

18 I'll start with a broad topic for our
19 discussion today and then we can drill down. So, I'll
20 toss this out to the entire panel. What trends do you
21 see in the future of big data? Is it going to get
22 bigger? Is it going to be better? Will there be more
23 passive collection of data versus active collection of
24 data? How will it be used, such as for marketing, fraud
25 detection or eligibility determinations? And should

1 consumers be concerned about these practices?

2 MR. MACCARTHY: Let me jump in. Is the mic on?
3 Can you all hear me?

4 AUDIENCE: Yes.

5 MR. MACCARTHY: Good. So, I first want to do
6 some marketing. Our friends at the Future of Privacy
7 Forum and the Anti-Defamation League have published a
8 nice little collection of examples where big data is used
9 for empowering people and promoting economic and social
10 opportunity. I urge you all to take a look at it and
11 contemplate the advantages, the benefits of using big
12 data in many of these contexts.

13 The couple of examples I want to mention, one
14 of them has already been mentioned, alternative data
15 scores, I think these are going to increase going into
16 the future. A recent study by LexisNexis found that 41
17 percent of Hispanics and African Americans could not be
18 scored by traditional systems, while only 24 percent of
19 the general population could not be scored. That's an
20 unscorable rate for minority populations almost twice the
21 general population.

22 Their new risk view scoring methodology allows
23 81 percent of the people who are not scored to receive a
24 score and thereby be eligible for the mainstream
25 financial products. That's one example. You heard a

1 little bit about that before, but I wanted to put that
2 one on the table as well.

3 Cognitive computing in healthcare, IBM has a
4 version of its Watson computer that functions as an
5 oncology diagnosis and treatment advisor. It's in use
6 today at Memorial Sloan Kettering and MD Anderson Mayo
7 Clinic is using it to select subjects for clinical
8 trials.

9 So, how does this help the under-served? Well,
10 there are shortages of specialty providers in hospitals
11 all over the country. Some 50 to 60 percent of community
12 hospitals do not have an oncologist on staff. But now
13 suppose that the medical insights from these computing
14 systems can be made available to clinicians in community
15 hospitals throughout the country. This isn't happening
16 today; it's a potential for the future and it's one I
17 think we should encourage.

18 The last example was one that was also
19 mentioned on the last panel. These are predictive
20 analytics in education. Many schools are using
21 predictive analytics tools to find students who are at
22 risk of dropping out so that they can engage in early
23 intervention operations. Many companies provide these
24 kind of tools. They're very, very effective. If they're
25 deployed in time, they can reduce the dropout rate

1 significantly.

2 So, three examples of the use of big data
3 analytics for productive and for socially beneficial
4 purposes that have the effect of increasing social and
5 economic opportunity. We'll have a further discussion
6 about all of these, I'm sure, as we go on.

7 MR. ACQUISTI: Okay, I'll do some marketing as
8 well like Mark just did. Curtis Taylor is an economist
9 at Duke, and Liad Wagman, an economist at Northwestern,
10 and I just finished a manuscript reviewing the economics
11 of personal data and the economics of privacy.

12 So, it was interesting, this exercise we did,
13 because we were looking to see what economists over the
14 last 20 or so years have said about the impact that
15 personal information and the trade of personal
16 information can have on the welfare and allocation of
17 surplus. Because, to me, going back to your question
18 about what is the next big issue -- for me, as an
19 economist, the next big issue is to what extent the data
20 will increase the economic pie, will lead to more economic
21 growth, benefitting everyone. So, a win-win. And to
22 what extent instead will simply affect the allocation of
23 surplus. So, winners and losers.

24 The economic pie remains the same. But some
25 entities gain more of the pie and some entities gain few.

1 So, for an economist, that's a problem of welfare and
2 allocation. And what we found in the detailed chart is
3 that, well, generally, with more information, economic
4 growth goes up, you have more efficiency and that is
5 predictable, I would say. But there are also cases where
6 paradoxically or surprisingly it's actually privacy which
7 can lead to more economic growth.

8 One case in point is health privacy
9 legislation, which can paradoxically promote innovation
10 in the field of HIE, health information exchanges,
11 promoting the growth of HIEs, because it decreases
12 privacy concerns and uncertainty that firms or health
13 organizations may have in terms of how to use their data.

14 In terms of the allocative effect, we find
15 evidence of, of course, both privacy and lack of privacy
16 affecting winners and losers. Sometimes it's the
17 transfer of wealth from data subjects to data holders, for
18 instance, the case of price discrimination. Sometimes
19 it's an issue of transfer of wealth between different
20 data subjects.

21 One experiment that we actually ran at CMU --
22 maybe I'll mention more about it later -- was about the
23 role that personal information found on social media can
24 have on the hiring behavior of firms. And what we find
25 is that even when candidates have identical educational

1 and professional backgrounds there is an impact on the
2 personal information, protected traits such as religion
3 affiliation or sexual orientation in how employers make
4 decisions.

5 So, this personal data, which employers can
6 find online, can paradoxically create less fairness. So,
7 we have more data, but less fairness. We have, of
8 course, also cases of more data, more fairness, which I
9 believe Cynthia will discuss.

10 So, the point being that going back and echoing
11 some of the remarks Chairwoman Ramirez said this morning,
12 not only I believe thst, as she pointed out, big data will
13 probably have both positive and negative consequences,
14 but I also believe that market forces alone will not
15 necessarily weed out the bad from the good, because what
16 we see in the literature is that market forces can create
17 both the bad and the good.

18 MS. DWORK: Can I jump in here? This is not
19 advertising. Maybe it's a call to arms. So, instead of
20 answering the question of what trend do I see, here's a
21 trend I would like to see. I would like to see big data
22 being used to detect discrimination. I'd like to see big
23 data being used to find ways of countering
24 discrimination. I'd like to see big data being used to
25 analyze how people behave and know how to make

1 suggestions to make their lives better. And much of the
2 talk on the previous panel was somewhat defeatist in this
3 regard.

4 And I think that danah is right, that we need
5 advocacy. We need somebody who has an interest in it.
6 If we rely only on people who have a financial well-
7 being, how are they going to get organized, in this
8 particular case, to help themselves?

9 MS. DIXON: Hi, thank you to the FTC for the
10 invitation. I appreciate the opportunity to talk about
11 this issue, which is very near and dear to my heart.

12 So, I've really thought about this issue an awful
13 lot, for a lot of years now, and early this year Bob Gellman
14 and I put out a report called The Scoring of America, and
15 a lot of our thoughts are distilled into those 90 pages.
16 And it took 90 pages because big data is really in a
17 formative phase right now and there are a lot of
18 signposts that point to this. But I want to really dig
19 at the root of the matter here and start there and in my
20 comments today move forward from that.

21 But, to me, the root of the matter is this --
22 and we really see a lot of things hedging around this,
23 but never really diving down and getting to it. So, to
24 get to it is this: The moment that a person, an
25 individual, is put into a category or is classified in

1 some way or is scored in some way, that triggers a data
2 paradox. We can talk about it all we want and I'm happy
3 to talk about it with you for hours. I can tell you many
4 examples where "big data" has been used to help
5 consumers. I can also give you examples where the exact
6 same data has been used to hurt consumers. And that is
7 the data paradox. If you're a scientist, you may call it
8 the classification effect.

9 But bottom line, when you classify an
10 individual, you trigger this. And when that is
11 triggered, we have to do something about that in terms of
12 fairness structures. And one of the very big question is
13 what do we do.

14 So, if you look, for example, at victims of
15 domestic violence, so in order to assist victims of crime
16 and domestic violence, they are put into a classification
17 as a victim of that crime. But if you talk to
18 individuals who are victims of these crimes, they don't
19 want to be in that classification because that reaps some
20 very difficult probabilistic analysis down the road and
21 they feel the effects of that, for example, when they pay
22 higher health insurance rates because they've been the
23 victim of a crime and they're assigned statistical risk.

24 People who have diseases and rare diseases and
25 chronic health problems have the same problem. So, at

1 the same time, you can use the information to suppress,
2 to lead, to help, to heal, to hurt. So, how we solve
3 that problem of that data paradox is going to be really
4 what we need to get at moving forward in big data.

5 DR. TURNER-LEE: Thank you to the FTC for
6 having me here at this conversation and to all of you for
7 attending.

8 So, I want to jump in. I think a lot of people
9 have already said some of the things that I want to say,
10 but I want to answer Tiffany's questions around trends in
11 the future of big data. Is it going to get bigger and is
12 it going to get better? And I want to say, yes, yes and
13 yes. I mean, every day we get out -- you know, I'm sure
14 it was said on the first panel, but every day we get tons
15 of data, individual bits of data collected about us that
16 goes into a dossier or portfolio that, in some way, has
17 an impact. And for social scientists like myself, who my own
18 plug is just working on a paper on privacy and minorities, we
19 don't know where that data is going in terms of its
20 social benefit, but, nonetheless, it's being collected
21 and it's being collected in an exponential manner.

22 I just attended a brief conference on the
23 internet of things and Cisco has basically stated that
24 the U.S. has a \$4.6 trillion stake in the internet of
25 things and the internet of things will only be successful

1 the more data that we collect around the use of those
2 devices.

3 It's interesting when I think about data
4 analytics -- and I recently participated in a panel where
5 the question was, is there a good purpose for big data
6 and data analytics and data science? Clearly -- and at
7 MMTC, we represent under-served communities, particularly
8 minorities and other vulnerable populations -- data
9 analytics can certainly generate a social and community
10 benefit. When I think about healthcare and how it can
11 contribute to that -- I know we'll talk a little bit
12 about that, so I won't go too far into it or educational
13 outputs of value -- big data can, in some way, actually
14 help us solve social problems related to health
15 disparities, educational disparities, consumer --
16 disproportionate consumer impacts, et cetera,
17 environmental causes.

18 One of the examples that I commonly use is when
19 you look at smart meters and low-income communities where
20 people tend to pay higher in terms of their rates,
21 there's a potential for big data to help us understand
22 better how to preserve income in the pockets of people
23 who are, you know, economically depressed. But at the
24 same time, create healthier communities and more
25 sustainable communities.

1 All that is great, right? Even with education,
2 there's the opportunity to adapt the technologies and I
3 think some of the things you talked about in terms of
4 predictive analytics, to help us to better educate low-
5 income minority kids. Again, that's all great.

6 But as I said on a panel earlier or last week
7 Mark was on the panel with me -- the data must be
8 protected and aggregated in such a way because,
9 oftentimes minority groups are holding on so tight to the
10 one asset that they have, which is their identity, and we
11 often see that if improperly used -- and I think
12 Alessandro's paper was actually very good -- we can see
13 bouts of discriminatory behavior that actually impacts it
14 negatively.

15 So, take the energy example that I just gave,
16 whereas big data could be used for the purpose of
17 building more sustainable communities, it can also be
18 used to tell low-income people that you're not using your
19 energy too smart and possibly there's an opportunity for
20 a surcharge. Whereas predictive analytics in education
21 can actually be a good thing to help educators teach
22 better and parents be more engaged, it also suffers the
23 possibility of redlining students in the classroom.

24 So, we have to think really carefully about
25 this. And we, at MMTC, constantly struggle because we

1 see the value of innovation and what it's actually done
2 in this society, while at the same time, for
3 disproportionately minority, senior, low-income
4 vulnerable populations, the question is can big data
5 produce a social benefit without having a subsequent harm
6 on those communities that are contributing to this. And
7 we've seen, particularly the FTC, examples where some of
8 those -- and I'm sure we're going to talk about it more
9 on the panel because we talked that we would -- but we've
10 seen examples where that discriminatory behavior has a
11 short-term impact and what we fear is a longer term
12 impact when it comes to civil rights.

13 MS. GEORGE: Stuart, I'm sure you have
14 something you want to say.

15 MR. PRATT: Yes. So, I was invited late to
16 this panel, so I missed the conference call. And
17 Maneesha called me and said, Stuart, we'd like to have
18 you on a panel, but we've already held the conference
19 call. And, so, I guess I get to say whatever I want
20 because I'm not bounded by whatever was on the conference
21 call. No, so, but I was on an alternative scoring panel
22 earlier this year -- Pam and I were on the panel together
23 -- and I'm glad to be back again.

24 Joe, I'm missing you here on the panel. So you
25 were on the first one, and taking good notes.

1 So, I love this dialogue. It's a really,
2 really important dialogue. It's really important that we
3 wrestle with fairness and fair treatment. And that's
4 true for industry organizations, that's true for
5 academics, that's true for some of the nation's largest
6 and most successful companies in the United States. And
7 you've got a great sort of cross section of interests at
8 a table like this. And, candidly, really the best hope
9 we have coming out of this is that we don't just sit on
10 this panel facing outwards, but some day we're sort of
11 sitting around the table looking at each other and having
12 more of that dialogue.

13 But, Tiffany, thanks for pulling this panel
14 together and for leading our discussion.

15 So, CDIA is much more -- our members, as the
16 Consumer Data Industry Association, we're much more
17 focused on risk management. So, it's a -- we often are
18 operating data systems, databases, which are a little
19 closer to laws we have on the books today and we're a
20 little further away, if you will, from the question of
21 how you categorize consumers in order to reach them with
22 the right offer. There's some of that. But we're more
23 often dealing with and pushing data into the transaction
24 with regard to how am I treated once I'm heading into
25 that transaction.

1 So, for example, the Equal Credit Opportunity
2 Act, very important law which addresses core fairness
3 questions relative to credit, of course. The Fair
4 Housing Act, which addresses core questions relative to
5 how I'm treated. But by the way, interestingly enough,
6 both ECOA and Fair Housing also address, to some extent,
7 advertising. They have implications for what do I say
8 when I advertise, where do I advertise. So, there are
9 implications. Certainly, current laws wrap around at
10 least some of the dialogue that we listened to -- and I
11 thought it was a great, you know, first panel -- but
12 those laws are out there today.

13 And I do think that that's part of the analysis
14 going forward. You know, how do current laws address
15 fairness and how sufficiently protective are they in some
16 of these transactions? Because our members are involved
17 in a telecom company's approval of a consumer, an
18 insurance company's underwriting a decision, a lender's
19 decision to make a -- what we'll call a risk-based offer
20 of credit and, of course, we've talked a lot about credit
21 scores and they're a rank ordering system. And, in fact, we
22 think it's a very effective rank ordering system and it's
23 important for us to have systems that rank order risk.

24 Why is that? In the United States, we might
25 lean towards safety and soundness because, in fact, the

1 great recession would tell us safety and soundness is a
2 whole lot more important than maybe we ever thought and
3 we actually could break the system here in the United
4 States and we got pretty close to it.

5 If you go to Europe, they would say credit
6 reporting systems, data systems like those that the CDIA
7 speaks for, are very important because we want to make
8 sure consumers have the ability to pay, that there's a
9 responsibility associated with the loan or the offer that
10 you make to make sure that it isn't just going to work
11 for you, but it's going to work for both of you in the
12 contract, that the consumer is also successful and it's a
13 good match. So, I think data is best when it's matching
14 the consumer with a -- not just any offer, not just an
15 offer I'm interested in, but an offer that I'm going to
16 be successful in accepting and working with going
17 forward.

18 That's a little idealistic. I'm not sure we're
19 100 percent there. I see Nicol leaning in towards me
20 here like this. But I don't know that we're 100 percent
21 there, but that's kind of the promise that we have. But,
22 for us, it might also be a great example real world would
23 be, we think more often now about not -- certainly, many
24 protected classes of consumers through the Civil Rights
25 Act and, by definition, through ECOA and other similar

1 laws, insurance commissioners at the state level, but
2 it's also about identifying consumers whose behaviors
3 have changed because of the economy.

4 My grandparents lived through the -- you know, the
5 failure really, not just a recession, but a full-blown
6 depression, and you could see the behaviors that they
7 had. But you know what, I look at my sons going through
8 college now and young people that we hire in our offices
9 and we look at the fact that debit card transactions have
10 overtaken credit card transactions, we see some shifts in
11 demographic behavior in databases today.

12 And so, what -- let's just take a credit
13 report. What a credit report looked like at one time may
14 look different going forward and how we inform the
15 dialogue of a risk-based decision may look different
16 going forward. The fact that I own something may be more
17 important going forward than how I pay a credit card
18 transaction or we need to bring new data in to thicken up
19 systems and to create more inclusion.

20 So, I do like the idea, though, that there are
21 market forces, which are lining up pretty nicely, with a
22 societal interest, deep societal values that we have in
23 this country. And that is we want fairness, we want
24 equity, we want equality, we want the right treatment for
25 the right consumer. And there's an interest in doing

1 that because it's, you know, sometimes, to some extent,
2 law, but also because of market interest. This broadens
3 our markets for consumers to engage in a successful
4 product.

5 And, again, it's the 50 or 60 million sometimes
6 called credit invisibles in this country. How do we
7 reach them? Well, we need public record data sources.
8 We need utility information because some consumers pay
9 utilities, but they may not be paying on a credit account
10 of some type. We need telecom because telecom is
11 ubiquitous and deeply penetrated into communities of
12 color in this country and used properly, used wisely,
13 used effectively, used fairly. These systems are the
14 kind of systems these data sets and the analytical tools
15 to back them up are going to empower consumers and we
16 will push deeper, but successfully into these markets,
17 successful for those communities and also successful for
18 sort of economic benefits very broadly. So, food for
19 thought.

20 MS. DIXON: So, to pick up on Stuart's
21 comments, the -- actually having you on this panel, I
22 think it's a great idea because regulated industries are
23 already using little bits and pieces of things that are
24 working, such as the Fair Credit Reporting Act and, for
25 example, HIPAA and folks who are regulated by the common

1 rule, people who are doing human subject research.

2 So, there are pieces that are working, and
3 we've learned a tremendous amount about certain
4 statistical populations because of the credit report and
5 credit scores and the 50 years of history that we have
6 there. Now that it's more public, we know more and
7 consumers can also benefit from that knowledge.

8 But I want to pick up on something that Stuart
9 was talking about, which is factors. So, let's say that
10 we have the Equal Credit Opportunity Act, and it has
11 narrow applicability, but factors such as race, whether
12 or not you're married, things that really matter in
13 those, you know, financial decisioning processes, they
14 matter in other decisions, too. And when you look at
15 large rich data sets, it's really a trivial matter now.
16 Data is a commodity. It is a commodity, which means you
17 can buy whatever data you want pretty much whenever you
18 want it to some degree. So, given that it's a commodity,
19 you have all of these what would be protected factors in
20 very rich data sets and they're being used for all sorts
21 of decisioning purposes.

22 A good example of this is what I call proxy credit
23 scores. They're not formal credit scores because they're
24 not using the same kind of credit report data that is
25 regulated, but they're using other factors that mirror

1 that same data. And, so, let's say you've taken out all
2 clear indicators of race or maybe even marital status,
3 there are other inferred factors that will then be in the
4 data that will -- or can be used to do exactly the same
5 thing. So, you take out one and it's like a jack-in-the-
6 box, another will step up. And this is how large data
7 sets become really problematic for ensuring privacy and
8 fairness, because you have all of these redundant factors
9 again and again and again in the data.

10 And how we focus on correcting for that problem
11 is very, very important because, right now, we're not,
12 not in very many situations. There's not one global
13 solution right now that corrects for that problem,
14 because that is not regulated data. So, we've got to
15 focus on that.

16 MS. GEORGE: Let me just piggyback a little bit
17 on what Pam just said about the richness of the data set.
18 I understand that, for some communities, their
19 information may not be included appropriately in the data
20 sets because of the way they use or don't use technology.
21 Does anyone have thoughts on why that is and how it can
22 be addressed? Nicol?

23 DR. TURNER-LEE: Well, actually, I was going to
24 separate into that, that puddle there. You know, I think
25 that's an interesting piece because we often think about,

1 you know, in these conversations, for those of us that
2 are entrenched in the telecom space, you know, broadband
3 adoption here, data here, you know, broadband-enabled
4 applications here and actually all these verticals cross,
5 at some point, to give us a rich robust conversation and
6 story, right, on how all these things interface. And I
7 would say, given -- I'll give a shout-out to the Center
8 for Data Innovation who Daniel -- I saw him here -- who
9 published a paper I didn't get a chance to read, but I
10 got a chance to read it over the weekend on data deserts,
11 and I'm sure he'll talk about it later, but if you think
12 about the disparities in broadband adoption, you have 30
13 million plus people that are offline that are not
14 contributing in any way possible to this ecosystem. To a
15 certain extent, you also have people who don't have, as
16 my buddy John Horgan has mentioned, the level of digital
17 readiness to actually go online and engage in a very
18 participative way on the internet for, you know,
19 noncommercial value versus commercial value, et cetera,
20 you put all that together -- and, I mean, I was thinking
21 about your comments, Stuart -- you might begin to see
22 some segmented marketing to some of those folks because,
23 you know, you have the others, the sociologists, the
24 perspective that my online behavior may match what I do
25 offline. And, so, I may be looking for, you know,

1 something that I may not perceive to be predatory in the
2 offline space translates to what I'm searching in the
3 online space, which then leads to some type of predictive
4 marketing in the types of products and services that I
5 use.

6 So, I think we have to solve that problem. And
7 I constantly tell people the broadband adoption digital
8 divide issue has not gone away, because I think when you
9 have the dearth of data particularly for vulnerable
10 minority populations and data is driving certain
11 decision-making and driving certain efficiencies, you
12 then disadvantage a whole group of people that, in some
13 way, to your first question, right, could benefit from
14 the positives of big data. They get left out or their
15 results get skewed because the proportion of people that
16 are participating may not have these other factors that,
17 you know, the literacy and the readiness at hand to
18 equally participate.

19 So, I think the inclusion piece, you know, the
20 Center for Data Innovation, just a last point, calls it
21 the data divide, you know, it still goes back to the data
22 and inclusion divide on how you look at this big picture.

23 MR. PRATT: So, I would add that one of the
24 approaches our industry has taken, though, whether it's a
25 fraud prevention tool -- and by the way, we live very

1 much in the fraud prevention world and in the -- sort of
2 the ability to pay world and really everything -- all
3 that data that flows into that transaction, for example,
4 where I've made an application. Of course, it's a
5 question of what application am I making and when did I
6 learn about it and those sorts of things as well.

7 But we sometimes look for -- I'm going to use a
8 term that we've used at CDIA -- necessary services, so
9 ubiquity. In other words, there is a question of that.
10 In other words, when you pick new data sources and you're
11 trying to use a new data source, you want a data source
12 that is broadly used. And, so, utility data is, by
13 example, a type of data because virtually anyone who has
14 -- no matter where you live, you are likely paying for a
15 utility of some sort. It could be very straightforward,
16 you know, water service and this sort of thing,
17 electricity, and then telecom is an example of, again,
18 where you have a fairly ubiquitous set of data. You're
19 pushed deeper into communities that are economically
20 disadvantaged who may not actually be engaged in a lot of
21 the other types of credit activities.

22 I serve on a World Bank task force. We talk a
23 lot about this. In fact, we're flying in probably 30
24 central bankers to Dubai for a meeting to talk about data
25 sets that can be used in various parts of the world to

1 create SME-based lending, which is often, you know, small
2 to medium enterprise lending, but it ties in with really
3 personal loans as well. It's almost the same thing as
4 conterminous in a lot of places. But the idea is what
5 data sets are out there. Colombia, for example, not
6 South Carolina, Colombia uses telecom data widely.

7 By the way, the Credit Builders Alliance is a
8 great group to take a look at when it comes to trying to
9 segment the population of consumers who may be credit
10 invisible. So, for example, Credit Builders Alliance
11 focuses not on the under-banked, but really on the
12 unbanked, those consumers who probably have the greatest
13 financial stress in their households. And there's a
14 group called Axion down in San Antonio, Texas, and
15 they're experimenting with different data systems, which
16 are interactive with the consumer, to try to build a data
17 set which allows them to predict success.

18 CBA aggregates these small loans that are
19 urban-centered loans, that are often minority-focused
20 loans, that are sometimes tribal-lending systems as well,
21 and that data flows back into traditional credit
22 reporting systems, for example. We have other members,
23 for example, who aren't running a traditional credit
24 bureau, but have stood up completely new data systems --
25 Mark discussed one of them -- where we can reach new

1 populations for the first time using entirely different
2 data systems that aren't just simply built off of a
3 traditional credit report, that are built otherwise.
4 And, in fact, I think five or six of our members, along
5 with CBA, we sponsored a symposium on this earlier this
6 year. It was hosted by Pew, but it was run by Credit
7 Builders.

8 I think it's a pretty good intense dialogue
9 and, obviously, you know, dialogues like this inform our
10 thinking in terms of how we go forward and what are some
11 of the framing issues. But I do think when you have an
12 Equal Credit Opportunity Act, a Fair Housing Act, even
13 universal service pressures that are put on the telecom
14 industry, those drive industries to think about whether
15 they have a Community Reinvestment Act obligation or not,
16 it drives industries to think about how do I reach
17 communities that are harder to reach otherwise and in
18 what way.

19 Under-banked have different needs than
20 unbanked, depending on definitions. Under-banked have
21 different needs than middle class consumers, though, who
22 are still living in very tight circumstances. And, so,
23 as you move through societal tranches of consumers, the
24 kind of data that we have allows us to work through that
25 and to, again, match up a better offer, we hope, an offer

1 which leads to success on both sides.

2 MS. GEORGE: Okay. So, I want to talk a little
3 bit more about this notion of privacy, which some of you
4 have touched on. And we've heard some mention in the
5 comments to this workshop about the role of data-
6 obscuring technologies or techniques or privacy-enhancing
7 technologies, such as de-identification. Is there a role
8 for those types of techniques going forward and are there
9 some that are better than others? I know Cynthia wants
10 to say something.

11 MS. DWORK: I think that privacy and fairness
12 are completely unrelated and simply don't understand what
13 de-identification would have to do with this discussion
14 at all. But going back to privacy or questions of hiding
15 information from the classifier, as Alessandro said, I do
16 have some examples there.

17 So, if you have a really well-trained
18 classifier and if you want to train a classifier well,
19 you want to give it as much information as possible. So,
20 for example, hearing voices may be diagnostic of
21 schizophrenia in one population, and in another
22 population, it might be part of a common religious
23 experience.

24 You could have, theoretically, a minority group
25 that is -- in which bright students are steered toward

1 mathematics and you might have a majority population in
2 which the bright students are steered toward finance, and
3 if the minority is very small compared to the majority
4 and you're looking for a quick and dirty classifier to
5 find bright students, you might just look for finance.
6 But that would be neither fair to the minority, nor would
7 it be giving optimal utility because you would miss out
8 on the gems in the minority.

9 And, so, there is a role for using as much
10 information as possible, and withholding information
11 would be inappropriate in those contexts.

12 MS. DIXON: Well, you know I've got to respond
13 to that, right?

14 MS. DWORK: Go for it.

15 MS. DIXON: Okay. So, I do think privacy and
16 fairness are aligned and very important in fundamental
17 ways. But I think it is in ways that are actually
18 surprising when you start to think about them at the
19 deeper levels. So, let's look at large data sets and
20 analytics in terms of, you know, the structures that can
21 govern some of the new things that are happening. So,
22 fair information practices -- well, wait, let me take a
23 step back.

24 So, first off, I said earlier that big data is
25 immature. It is. It is immature and there are two

1 really big markers that tell me that it is an immature --
2 in an immature state. Number one, there is no firm
3 scalpel-like legislative definition of big data. Now, I
4 know what big data is, we all do in this room, right?
5 But show me an actual legislative definition of it, and I
6 know that you can't right now because there isn't one
7 yet. There will be, but not yet.

8 So, the second thing that indicates that big
9 data is currently a bit raw and unformed is there are no
10 global solutions to the various problems that it poses.
11 Right now, though, there are focused solutions and what I
12 would call also local solutions to specific problems,
13 surgical strike solutions, and there are also ways of --
14 so, those are the two things that exist. But how do we
15 -- so, we're clearly at a formative stage. So, what do
16 we do with that?

17 We can't just throw out the existing fairness
18 structures. Some have said, oh, big data, okay, let's
19 just push everything aside and let's start from scratch.
20 I don't think that's necessary or appropriate at all. We
21 need to use the existing fairness structures that we
22 have, Equal Credit Opportunity Act, Fair Credit Reporting
23 Act, HIPAA, the Common Rule, the Belmont Report, the
24 Nuremberg Code. These are ethical codes, of course. And
25 then, of course, the Fair Information Practice

1 Principles, these are very important. We can't just toss
2 them out because there are some weird things happening.
3 So, we need these old structures.

4 And on top of that, to address your question,
5 what do we do, we need to look at what do we do in terms
6 of what I would call statistical parity. We have to have
7 statistical parity, statistical fairness. And there are
8 ways of achieving that. So, it's these fairness
9 structures and statistical parity.

10 So, for example, Stuart said something very
11 compelling about how you're choosing the data sets. That
12 is part of statistical parity. Where are you getting
13 your data? Was it from people who volunteered this data
14 or was it coerced? Was there mandatory classification of
15 people? Was someone put in a box in a mandatory way that
16 they maybe didn't want to be or didn't know about? So,
17 these are all very significant considerations in how we
18 deal with the fairness and privacy piece, because there
19 is information that is so deeply prejudicial that it
20 really is a classifier killer.

21 So, for example, if someone is found to have
22 HIV/AIDS, it really breaks a lot of the classifications
23 that they're in and really impacts the outputs. And in
24 other language, that might be called sensitive
25 information, but it's also highly prejudicial, and we

1 need to really understand that privacy has a role in this
2 because there is some information we need to think about
3 not collecting, and if we do collect it, we have to
4 protect it. HIPAA was right in how it handled that. It
5 handles medical research for human subject research
6 protection, there is very meaningful robust consent in
7 what's called an IRB process, Institutional Review Board.
8 And, so, there are examples already in place where we can
9 go.

10 MS. DWORK: So, first of all, having worked for
11 more than a decade on privacy preserving data analysis, I
12 don't want anyone to think that I don't care about
13 privacy. I do care about privacy. I'm just saying that,
14 intellectually, mathematically, privacy and fairness are
15 not necessarily the same thing. What you're talking
16 about is the inability of the people who are making
17 decisions to disassociate certain pieces of information
18 from the decision. And what is really going on here is
19 that you're searching for -- and very, very appropriately
20 -- you're searching for some kind of a measurement for
21 any particular classification test, you're searching for
22 a way of measuring how similar or dissimilar are two
23 people for this particular classification task.

24 MS. DIXON: That's right.

25 MS. DWORK: And quite possibly, the very best

1 measurement that society and math together could come up
2 with would involve all sorts of factors. But you don't
3 trust the people or the machines or whatever that are
4 making the decisions right now to give them all of the
5 information, and that's probably very reasonable.

6 MR. MACCARTHY: So, let me jump in here. I
7 think this -- you know, this is a very abstract and
8 almost philosophical question. If you look at some of
9 Cynthia's work, I was just telling her she defines this
10 concept of relevant similarity as a way of first saying
11 do that and then go into maximizing utility. We've heard
12 that before. Immanuel Kant said that in his theory about
13 ethics. So, we're dealing with some pretty abstract and
14 philosophical questions when we come to this stuff.

15 And at the level of social policy, at the level
16 of what we think is fair and what we think is just, I
17 think a lot of the discussions we're having here, they
18 may seem to be about data and how to interpret data and
19 so on, but I think they really go back to some of these
20 basic ethical and philosophical questions. So, I do
21 think we need to take a step back and not to think about
22 these issues as if they were issues about data and
23 analytics, but they really are pretty broad social
24 questions.

25 So, for example, do we need to have a special

1 social policy towards big data? My instinct is no, big
2 data is just an evolution of what's been going on in the
3 data analytics world for generations and to think we need
4 to have a special set of laws or best practices just to
5 pick up the big data subset of all data analysis, I think
6 is the wrong direction to be thinking about. I do think
7 we need to focus not on kind of global solutions to all
8 these problems, but to go back to the specifics.

9 As Stuart's been saying, you know, there is a
10 well-developed body of law that surrounds certain uses of
11 information and we've chosen to put that body of law in
12 place because we think, in those areas, concerns about
13 social policy are the greatest and, so, we need a large
14 sort of set of protections for that.

15 In other areas, where Mallory was talking about
16 sending catalogs to men rather than to women or
17 advertisements for cars that appeal to men, our social
18 concerns are a whole lot less. So, the idea that we
19 would have one set of rules, one set of fairness
20 requirements, one set of access requirements that goes
21 across all data uses, I do think that's the wrong
22 direction to go in.

23 DR. TURNER-LEE: So, I want to jump in because
24 I think I agree, to a certain extent, though, with
25 regards to having some framework, though, of what

1 transparency and the purpose of your data looks like. I
2 mean, I'm a big fan of the FIPPS, to a certain extent,
3 when it comes to privacy concerns, because I think that
4 people have to understand that their data is being used
5 for particular purposes.

6 And in the internet, while I agree with Stuart
7 that you actually have different bodies of policy buckets
8 and privacy parameters that actually define how your data
9 is being used, let's face it, the internet is this big,
10 big buffet of places that you can go. It's not that
11 simple any more to actually say, well, I'm going to the
12 internet for this or I'm going for that. You know,
13 people are going to the internet to engage in a multiple
14 range of activities that, at some point, get muddled
15 because it's not necessarily going into your Safeway and
16 giving your email address so that you can get benefits on
17 your grocery shopping at Safeway, right?

18 When you give your email address on the
19 internet, you know, there's a data information service
20 that is taking that information and creating algorithms
21 of where to direct you and how to advertise towards you.
22 There's probably a search that you did that brings up,
23 you know, a healthcare provider. You know, you might
24 have gone and bought red shoes and the next thing you
25 know you're getting red shoes advertisements, ladies,

1 right, for just one purchase that you made.

2 So, I think it's such a hard ecosystem to sort
3 of distinguish between this is why people are going to
4 the internet for this particular purpose. So, I think a
5 general framework, like the FIPPS, is actually
6 appropriate to help us figure out how do you
7 ensure that the input of data, whether it's big or, you
8 know, small data, does not impute cultural stereotypes as
9 well as cultural cliches that actually lend itself to
10 predatory behavior and actions on the part of, you know,
11 the online space. I think that's so important.

12 I mean, we've seen it with segmented marketing
13 where, again -- you know, again, for people of color --
14 and this is interesting because I'm doing a paper on this
15 -- from the long term, we've not been able to see the
16 exact civil rights infraction that happens because, you
17 know, someone has seen something on my Facebook page or I
18 put up a post. But it's going to happen. It's just a
19 matter of time that we're going to see that type of
20 predictive analytics or algorithms defined and, you know,
21 discriminate against people.

22 The question becomes, do most consumers know
23 that when they participate -- particularly for minority
24 consumers who over-index in social media when they are on
25 and over-index, you know, on the internet as new users

1 because they're experimenting, exploring and trying to
2 attain the aspirations of other internet users, do they
3 understand how their data is being used? Do they
4 understand what distinguishes their private personal
5 identifiable data from data that they're actually
6 basically contributing to the ecosystem, you know, just
7 because they want to be part of the conversation?

8 And, so, I think those are clear distinctions.
9 Again, it was brought up in your paper, Alessandro, about
10 that. But those are things that we look at at MMTC, you
11 know, will that have an impact on someone's ability to
12 get a job or healthcare or, you know, something of social
13 value, not necessarily their ability to stream content,
14 but something of social value that will essentially --
15 you know, when they are applying for a car loan, you
16 know, will give them higher rates, and I think that's
17 really important to put in this conversation.

18 MR. ACQUISTI: I wanted to connect what Nicol
19 just said to something Cynthia said and something Solon
20 this morning was mentioning. So, I'm ready to believe
21 that most of the times more data may decrease
22 discrimination, increase fairness, increase efficiency,
23 but it's also the case that the opposite may happen.
24 Some examples were given this morning by Solon talking
25 about when data mining discriminates, and the other point

1 was made by Cynthia when it is the human decision-maker
2 with his heuristics and biases, which makes incorrect or
3 biased usage of the information or even analysis made
4 available to him.

5 The case in point Nicol was referring to was
6 this experiment we did on the impact that social media
7 information has on the hiring behavior of a U.S.
8 employer. So, we did this experiment in which we applied
9 to over 4,000 American employers, we have CVs, resumes,
10 which were identical in terms of educational attainments
11 and professional achievements for different candidates.
12 However, we had also created social media profiles for
13 these candidates. So, we wanted to see whether employers
14 would go online and search for the personal information.

15 And employers did. And what was interesting is
16 that they would react to the personal information,
17 specifically to disclosure of a religion affiliation, in a
18 discriminatory manner so that our Muslim candidate was
19 less likely to be invited for an interview than our
20 Christian candidate, and this is a parity of professional
21 and educational background. So, this addressed a
22 potential problem sometimes with more information not
23 necessarily leading to more fairness.

24 There is also a broader story, which is the
25 huge tension that this kind of study shows between the

1 legislature who decided to have regulatory protections to
2 certain traits so that certain traits should not be asked
3 about in interviews or should not be used in the hiring
4 process and information, not just information technology,
5 which is effectively bypassing the legislation because
6 it's making this new data, these traits, these attributes
7 perfectly easily available to employers without employers
8 even needing to ask during an interview.

9 MS. DIXON: You know, there's a really
10 interesting idea here and I want to jump into the weeds a
11 little bit to explain it. So, earlier in my comments I
12 talked about the fact that when a person is classified,
13 it triggers the data paradox. And really we could spend
14 many hours talking about good big data and bad big data.
15 All examples exist from the top to the bottom of the
16 spectrum. We can take that as a fact and just move
17 forward with that.

18 And then here's the deal though. So, in
19 regards to your comments, Nicol, I was, you know -- one
20 of the difficult things that I was forced to
21 unambiguously assent to at the conclusion of the
22 researching of the scoring paper is that really we cannot
23 control our information flows any more, our so-called
24 digital exhaust. We really don't have the full rights
25 and tools to shape them right now. And one of the really

1 big ways this is happening is in retail transactions.

2 So, if you look at a lot of the data broker
3 lists and a lot of other data about how our data is being
4 gathered for classification, one of the big ways this is
5 happening is through the analysis of our retail
6 purchases, and it's like, okay, so who's doing this? Is
7 this just, you know, debit and credit card? How is this
8 happening and can I opt out? Is there a notice about
9 this? I think this is a very in-the-weeds specific
10 example of you don't have to be on social media to have
11 this issue impact your life. And we're talking about
12 long-term, you know, big patterns here. You know, is
13 someone purchasing over-the-counter medication? Is
14 someone purchasing wound care for someone who had a
15 serious injury? Is someone a diabetic because they
16 bought a magazine, you know, that may infer that?

17 And then we can game it on the other side. Did
18 you buy hiking boots? Did you go to REI? Are you
19 subscribing to a running magazine? Cool. This will help
20 your -- perhaps your health plan to charge you less. So,
21 you can game it on all sides.

22 But the question we really have to ask going
23 forward is what's happening here and what structures can
24 we use to ensure that there is fair information
25 principles that are encoded into all of these processes

1 from top to bottom, so that when we make a purchase,
2 we're confident that what we're buying, we can use our
3 credit cards, we can use our debit cards. We don't have
4 to run around like some crazed tin-foil hat person and
5 use cash for everything. That's not the answer. The
6 answer is fairness structures that protect our digital
7 exhaust and that give us the tools and abilities to shape
8 it.

9 I've actually been heartened by some of the
10 opt-out tools that I'm seeing that are pretty granular
11 and that allow us to see where we've been categorized and
12 then choose and alter our categorization. This is very
13 helpful. So, Acxiom has one of these. Their opt-out --
14 their data -- about the data portal. I went and looked
15 at my categories. I have very different categories
16 depending on which email address I use. And, so, I did
17 some granular opt-outs and feel much better about the
18 world. Now, I won't be seeing advertising for Asian men.
19 Someone thought I was an Asian man. I don't know how
20 they did that, but anyhow. So, categorization is a big
21 deal and it can really change how your life looks.

22 MS. DWORK: So, I'd really like to bring up a
23 paper here that just floated across my desk, and I'm
24 afraid I don't even remember the entire author set.
25 Anupam Datta was one of the authors. But it was a -- the

1 paper involved experiments that were done in which people
2 had changed their categorizations on Google and it did
3 not have the anticipated change in advertising.

4 MS. DIXON: Oh, interesting.

5 MS. DWORK: So, I'm sorry I'm not informed in
6 more detail, but I suggest that people look this up.

7 MS. DIXON: Yes. That's interesting.

8 MR. PRATT: You can see how in this dialogue
9 we're beginning to sort of categorize uses as well. In
10 other words, categorize -- and I think that's important
11 that we begin to unpack this dialogue and not allow big
12 data to just get squished together into a sort of
13 singular dialogue. The kind of data sets that a CDIA
14 member has are really -- they're not often -- and
15 certainly not for risk management purposes, kind of big
16 data that is derived from my search engine searches, the
17 websites to which I go.

18 There are some lenders that are experimenting
19 with the use of that kind of data. Consumers are
20 essentially opting in to do business with that lender.
21 It is important to know that that lender is still
22 obligated to live by the Equal Credit Opportunity Act.
23 So, even though -- so, there's an example of a lender
24 with kind of a closed system of data and the consumer
25 said, yes, you can use this data. I don't have

1 traditional data sets, you know, for you to be able to
2 make that lending decision. So, I do think that's
3 occurring.

4 Also, we haven't talked too much about it and
5 I'm not sure that these terms apply quite as often today,
6 but really structured versus unstructured data is also
7 part of the discussion. You know, unstructured data
8 might be data that's more so less directly identified
9 with me. It depends on whether you think an IP address
10 is personally identifiable information or not.

11 MS. DWORK: Yes, it is.

12 MR. PRATT: No, it's not.

13 MS. DWORK: Yes, it is.

14 (Laughter.)

15 MR. PRATT: And later, we're going to be doing
16 a little song and dance, it's going to be really good.
17 But I would argue that IPs can be associated with
18 individuals. But the question is, our databases that our
19 members build are still based on identifying information
20 of the traditional type because our members are building
21 -- if they're building a database for purposes of an
22 eligibility decision under the Fair Credit Reporting Act,
23 then they have to build the database along a certain set
24 of lines to make sure it's accurate and meets the
25 accuracy standard. And this kind of goes to the point.

1 So, one of the questions is whether you use the
2 FCRA as the template or whether you use a fair
3 information practices template of some sort, and there's
4 many of them out there, I tend to like APEC'S better than
5 some others -- you know, the question is when do you
6 apply the template and in how nuanced a way do you
7 apply that template to that kind of information.

8 So, there's a lot of advertising activity going
9 on out there. Our members -- like I said, our members
10 tend to have a structured data set. It tends to be built
11 off of identifying information. It tends to be wrapped
12 in a law, like the Gramm-Leach-Bliley Act. You can build
13 a fraud prevention tool to protect consumers, but it's
14 not going to stop a transaction, it slows it down.

15 Essentially, it's like going through the metal
16 detector and then having somebody wand you to make sure
17 that they really know whether or not you're carrying
18 something into the building versus eligibility. I want
19 to get into the building and I need to have a certain set
20 of credentials to get into that building and can I have
21 access to those credentials and how are they used and so
22 on.

23 We're a very use-based society, by the way. We
24 look at outcomes and we tend to measure data uses in
25 terms of the outcome, as opposed to trying to manage each

1 step of the process. I had a -- I was on a panel in
2 Berlin where, oddly enough, milk production was used as
3 the example here in terms of regulatory strategy. And at
4 least in Germany, this fellow, this economist described
5 the German government regulates every step of the process
6 in milk production. So, really it's a -- forgive the pun
7 -- a homogenized approach to milk production. You really
8 have no strategy by which you're going to be able to
9 remove cost from the market and be able to improve your
10 margin even if you have a very -- you know, a very
11 structured price structure on the back end.

12 Here in the United States, we don't tend to
13 regulate every step of the milk production process; we
14 test at the end to see if the milk is homogenized
15 properly, if it is -- meets the purification standards
16 and so on and so forth.

17 So, we're kind of getting deep into this very,
18 I think, almost philosophical discussion, as Mark termed
19 it, and I think that's right. What template do we use
20 for what type of use? When is categorization an issue of
21 harm, for example, might be one way to think of it. When
22 is categorization just a question of whether I got a
23 catalog that was applicable to me as a buyer of certain
24 products in the marketplace?

25 But I do think we're doing pretty well as a

1 country in terms of eligibility. When data is used as a
2 gatekeeper, that data is regulated by a fair information
3 practices structure under the Fair Credit Reporting Act.
4 When data is used for fraud prevention, there's a law
5 that wraps around it. When data is used in all those
6 transactions, there's quite frequently, in fact, very
7 definitively in the context of insurance and in the
8 context of credit and fair housing, in particular, and
9 the equal -- and then the EEOC as well, there are laws
10 which establish the baseline result that we expect, and
11 we expect to see a result which is fair for all, fair
12 treatment for all, and that we've even established,
13 rightly so, protected classes, because we have found
14 problems in our society where we did not identify these
15 protected classes.

16 MS. GEORGE: So, that's actually the perfect
17 segue to my next question, which was, as we move forward
18 in this era of big data and these new practices, what is
19 the model? Should it be based on use? Should it be
20 based on harm? Should it be based on data collection
21 methods, active versus passive? Like what are the
22 guideposts that we should be looking for as we emerge
23 into the future?

24 MR. MACCARTHY: So, let me quickly jump, if I
25 could --

1 MS. DIXON: I'll go next.

2 MR. MACCARTHY: Yes. I think you touched on
3 the two big ones, which are use and harm. This brings us
4 back to the, you know, very specific discussion of very
5 specific ways in which information is used and how people
6 can be damaged. And I do think we -- sometimes more
7 information is better in order to achieve the particular
8 outcome that we want. Sometimes more information is not
9 so good. I mean, there's the famous experiment, natural
10 experiment in why classical orchestras were all men for
11 years and years and years. It was because the conductor
12 would look at the people who are actually performing the
13 music and notice which ones were men and which ones were
14 women. But when you put them behind a barrier so you
15 couldn't tell what the sex was, suddenly, it became
16 50/50, you know. Withdrawing information, in that
17 particular situation, was something that was very helpful
18 in avoiding a discriminatory problem.

19 For many uses of racial and ethnic information,
20 the decision makers aren't even allowed to know about
21 race and ethnicity. So, we want to keep that information
22 secret. Maybe privacy there promotes fairness.

23 But sometimes more information is more. All
24 these products that we've been talking about, the
25 alternative data products, they require more information

1 about people in order to accomplish their good purpose.

2 The -- another example, and this goes back to
3 your point, will businesses and others, you know, try to
4 reach out and try to solve these problems? Well, most
5 companies want to have a diversity program where they
6 reach out to make sure that their workforce looks like
7 America and they want help to do it. There's a new
8 service provided by a company called Entelo that will use
9 information, social network information, information on
10 the web, it's in the FPF study, which I mentioned earlier
11 before. And the idea is using this kind of proprietary
12 tool, you'll be able, as a company -- be able to target
13 your recruitment efforts to try to get at the kind of
14 people who will be qualified for your work and yet will
15 satisfy your diversity requirements.

16 So, the uses of information, how much you need,
17 where it comes from, how it's used, those are all
18 relevant factors. I don't think there's a template,
19 there's no one-size-fits-all, here's how we do it all
20 circumstances and for all purposes. But I do think if we
21 pay close attention to the actual uses and the dangers
22 we're trying to guard against, we can make some progress.

23 MS. DIXON: So, great question, and I
24 appreciate your comments, Mark. They were very
25 thoughtful.

1 So, I want to talk about medical just really
2 briefly because it really does provide a really
3 intriguing example. So, if you look at the issue of
4 medical research, a lot of folks will cite medical
5 research as a perfect example of how to handle big data.
6 And, you know, medical research is intriguing on a lot of
7 levels. If you look at the various ways that the ethics
8 of how privacy works in the medical field are crafted,
9 it's absolutely fascinating.

10 So, to kind of dive in, if you look at human
11 research subject protection, that's where the strongest
12 medical privacy protections are, if you're doing research
13 that impacts human subjects. So, if you're federally
14 funded, you're going to be captured under something
15 called the Common Rule. The Common Rule is a regulation,
16 so that is regulated. You will have to get meaningful
17 consent from the individual in order to participate, and
18 it's all run under an IRB process.

19 That Common Rule is very complex and it was
20 built on something called the Belmont Report, which was
21 not a piece of legislation. The Belmont Report was built
22 on something called the Nuremberg Code, which was an
23 ethical code developed after the World War to prevent any
24 kind of human research atrocities from ever occurring
25 again. The Nuremberg Code had, as its absolute bedrock

1 foundation, human consent as absolutely the bedrock of
2 what has to happen in human subject research protection.

3 And even though the Nuremberg Code was an
4 ethical framework that didn't have legislative teeth, the
5 teeth it had is that it appealed to our humanity, and
6 that's what stuck. It stuck all the way through the
7 Belmont Report, it stuck all the way through the Common
8 Rule. And where we see it violated today, in certain
9 commercial instances, it strikes us, again, as an
10 unfairness.

11 So, it's very important that the ethical
12 frameworks are also considered in adjunct and in addition
13 to the regulatory frameworks that exist because they all
14 have something to add. And in cases where regulatory
15 frameworks do not apply because of narrow applicability,
16 we really need to look to the ethical standards because
17 they are human. They say something human about us and
18 it's what's really important to listen to.

19 MR. ACQUISTI: You were asking about what model
20 may work. I am on record as criticizing transparency and
21 control mechanisms due to a series of behavior
22 experiments we have run showing how, for instance,
23 control of personal data or even just a feeling of
24 control of personal data can lead to more risky
25 disclosures, over confidence, and more risky disclosures

1 and transparency is very ineffective in that I can read
2 something, understand it, and then that information is no
3 longer salient at the moment I have to make an actual
4 decision.

5 However, let me for once actually take the
6 defense of transparency, in fact push even the envelope
7 farther, kind of maybe a little provocation for the
8 panel, and focus on the concept of data provenance. What
9 if we start applying the rules of the data industry once
10 we use it on consumer data, we apply the same rules from
11 the consumers on the data that firms have about
12 consumers.

13 So, imagine a system where we -- every piece of
14 personal information held by any data holder has to be
15 attached to metadata showing the exact provenance of that
16 information, whether it is observational data, data
17 traded and received from another entity, or inferred
18 data. So, data predicted based on some algorithm, in
19 which case, also, the algorithm should be revealed.
20 If I am classified as a consumer who is willing to pay
21 \$80 for this good rather than \$40 for this good, I would
22 like to know why.

23 Considering the sophistication of the data, the
24 way it is presented to us, as nearly being able to solve,
25 in the close future, any societal problem, that kind of

1 technology, of attached metadata showing the provenance
2 of personal information is not really that far -- that
3 science-fiction-like. Otherwise, if you keep having big
4 data for consumers and only trade secrets for firms and
5 how firms use data, that's the kind of information
6 asymmetry which economic literature tells us will
7 reiterate rent positions and economic imbalances.

8 MS. GEORGE: We're drawing to a close here, so
9 I just want to remind the audience, if you have any
10 questions that you'd like to submit to the panel, we have
11 staff around the room who can collect your question
12 cards. And in the meantime, I'm going to pose one final
13 question to the panel before we start wrapping up.

14 So, on this notion of transparency and control,
15 there's been some suggestion that providing more control
16 to consumers is the solution to the problems of big data,
17 providing technology and techniques for consumers to be
18 able to control how their data is collected and what
19 happens to them. Are there limitations to that proposal
20 or is that the solution to this problem that we've been
21 discussing? And, Nicol, I want to start with you.

22 DR. TURNER-LEE: Yeah, I mean, this is a very
23 interesting question because this whole time I've been
24 talking about empowering consumers, right. But I think
25 it was mentioned earlier about this whole concept of opt-

1 out, right. And because there's going to be some data
2 that we need that have socially beneficial purposes, that
3 we would like most people to participate, energy being
4 one of them or any type of utility. We would certainly
5 want people to partake in it because it's a passive data
6 collection, not necessarily an active data collection
7 because we're essentially gathering information about the
8 utility use that will prove valuable to us in improving,
9 for example, the smart grid or other things in our
10 society.

11 At the same token, and this is a conversation
12 -- I was joined by several scholars, on the internet of
13 things, you know, when a person, for example, walks into
14 a home that is fully wired because of the internet of
15 things, your toaster, your refrigerator, your bed for
16 that matter, all registers personal data, do you have the
17 ability to opt out of that environment just because you
18 don't want, you know, people to see how often -- you
19 know, if you're like me, you don't make it to your bed
20 often because you're also reading papers and you're
21 sitting on your couch, right.

22 So, it's like, you know, at some point, I think
23 the conversation has to be made and I think we've all
24 touched on in some way to your earlier question, Tiffany,
25 about, you know, when we're coming up with a framework,

1 does it balance use versus harm, right, with allowing
2 some flexibility for the collection of data that will
3 help us for the purposes, again, of efficiency and public
4 good, and the extent to which consumers, you know, from
5 the front -- I mean, that's another -- when we start
6 talking about this -- and, you know, not to make this
7 long-winded, but when we start talking about this, when I
8 was at Joint Center for Political and Economic Studies
9 years ago, we did just a raw review of privacy policies
10 and we recognized that, in some cases, you had to have a
11 PhD or a JD just to read the privacy policy. You know,
12 after we ran them through the fluency indicator, you
13 know, the level of what people are engaged in is
14 sometimes not known, you know, in terms of what they're
15 actually getting into.

16 So, I think the opportunity to look at creative
17 solutions, like an opt-out or allowing people -- you
18 know, we should not have it where we look at consumer
19 protection when a bad actor, you know, comes to the play
20 or a bad action happens, because that's probably hardest
21 to actually reverse at that time, particularly for,
22 again, minority communities. When your credit is
23 compromised and you don't own a home or you don't have a
24 bank account, the biggest asset you have is your social
25 security number. Imagine what it's like for a senior

1 African American woman to have to repair her social
2 security and her credit, you know, because of an
3 infraction of harm.

4 So, we have to figure out ways for people to
5 have a lot more knowledge as to, you know, one, the
6 internet is a participatory environment and, in some
7 cases, you'll know when your data's being collected and
8 sometimes you won't, right. Two, when I feel that there
9 is some particular harm or some type of compromise in
10 terms of my personally identifiable data, in particular,
11 right, I have that decision to opt out. And, three,
12 going back to my earlier notion about the internet of
13 things, I have the ability to say I don't want my data
14 looked at if it's pertinent to me as an individual, you
15 know, and not necessarily something that's more pertinent
16 to the broader group.

17 So, I'll pass it over to you.

18 MR. PRATT: Thank you. Yeah, I think it's, in
19 some ways, an all-of-the-above strategy, meaning you
20 really need to look situationally at the nature of the
21 data and really fair information practices are not a
22 model --

23 DR. TURNER-LEE: Right.

24 MR. PRATT: Even if you were to look at a FIPPS
25 model, it's not monolithic. I remember working with the

1 GAO group a while ago. They were looking at government
2 uses of data and they applied an OECD FIPPS model, but
3 they did it in a really clumsy and sloppy way, and it was
4 really rigid and it didn't make a lot of sense. But I
5 think having framework models to trigger thinking and
6 create more sophisticated analyses and understanding is
7 very important, and I think a number of the academics in
8 this discussion already have introduced papers, as well
9 as thoughts, that suggest that data which seemingly is
10 neutral may not always be neutral or an algorithm which
11 we think is neutral may not always be neutral. We should
12 think about that, and that's part of our FIPPS model, if
13 you will. It makes a lot of sense.

14 But opt-out will work in some cases and opt-out
15 won't in others. A great example is years ago I remember
16 there was a -- one of the browsers had given me the
17 option of turning on a switch, if you will, so that I
18 could track cookies and I could decide which cookie I
19 wanted to accept and which one I didn't, except that
20 every time I went out onto the internet, my screen was
21 just covered with little cookie notices and it was almost
22 like pop-up ads. I mean, I was clicking and clicking and
23 clicking trying to get rid of all the -- you know, the
24 damn cookie notices. And before you knew it, I was not
25 reading the cookie notices; I was just doing battle with

1 them, right, to kind of -- so I could actually see what
2 was on the screen.

3 So, there would be almost like a behavioral
4 issue there for consumers, right. You know, how do
5 consumers behave and what is the -- what is your goal and
6 what's the most effective strategy to kind of get to that
7 goal. So, I'd say it's kind of all of the above and it's
8 nuanced and it's careful and it's thoughtful and it's
9 probative and it's not just simply this monolithic --
10 which is what I think is sometimes the problem with law.
11 Law often is too monolithic and too rigid and is applied
12 in a very sloppy way and it can be harmful.

13 A great example would be HMDA data, Home
14 Mortgage Disclosure Act data. If we're trying to
15 determine whether or not creditors are -- even if
16 creditors themselves are trying to determine whether or
17 not they have a practice which is facially neutral, but
18 is not in some fashion, it's hard to know that if you're
19 not gathering the data set that you need in order to then look
20 for that in order to decide, wow, okay, I
21 have something here that I couldn't discover in the first
22 place because I'm prohibited from gathering the racial
23 information that I might otherwise need. That's the
24 nuance of it, I think.

25 MS. GEORGE: So, I see we only have a few

1 minutes, so I'm going to ask if anyone has any final
2 thoughts because we don't want to keep people from their
3 lunch.

4 MR. MACCARTHY: The only quick thought I've got
5 is that this focus on use and harm is a really
6 alternative way of thinking about these things. If you
7 put too much weight on the alternative of giving
8 information to users, being transparent and then letting
9 them choose, that's really your focus and you're really
10 pushing that as your major defense against unfairness and
11 privacy invasions, you got to do it. In some cases,
12 human subject experimentation is not something we want to
13 sort of make decisions for people. But if that's your
14 universal solution, I think you're really doing customers
15 and consumers a disservice.

16 You're responsabilizing your own users, you're
17 telling them it's their problem, you figure it out.
18 Here's a bunch of data you don't know anything about or
19 how to interpret it, but I've given it to you and if you
20 want to opt out, go ahead, opt out. I think that's not a
21 productive way to protect people because the tendency for
22 people in that circumstance will simply be to throw up
23 their hands and do something else.

24 And on the other hand, if you make the person
25 who's gathering the data and using the data responsible

1 for fair and appropriate use, that I think points in the
2 direction of putting the responsibility more where it
3 lies, not simply on the data subject to protect himself
4 completely.

5 MS. DWORK: So, that actually comes back to the
6 point that I made at the very beginning. I think
7 everybody should be thinking all the time about, for
8 various kinds of classifications tasks, who should be
9 treated similarly to whom. And we have got to start, as
10 a community, taking responsibility for trying to lay out
11 those rules. This was done in the context of fair credit
12 reporting; it should be done in lots of other contexts as
13 well.

14 MS. DIXON: I don't think the structures need
15 to be reinvented or shoved aside because data sets are
16 larger. It's important to keep the regulations that we
17 have, allow them to apply where they're applying, to
18 ensure that fair information principles are applicable
19 and still relevant and still practiced, and we also need
20 to add statistical parity and we need to look at the
21 underlying ethics of the issues as well, because where
22 there are not frameworks, there still are underlying
23 ethics and we can't ignore them because some of the
24 problems that exist in the uses of this data are fairly
25 profound and there's a lot of discussion of, oh, well,

1 let's -- you know, let's throw out collection limitation
2 because it's too hard and let's just focus on uses. And
3 then there's discussion of, oh, well, let's not -- let's
4 not control uses, let's focus only on collection
5 limitation.

6 Look, right now, we're in a situation where we
7 have many multiple overlapping remedies and I think
8 that's going to be the case for quite some time and we
9 need to look at those remedies, really study them, see
10 where they're working and how, and look to see what's
11 important and what we need to focus on, where are the
12 real problems and where are the most disparities
13 occurring, and let's fix those and move through the
14 ecosystem with it.

15 MS. GEORGE: Alessandro, you have anything
16 else?

17 MR. ACQUISTI: In essence, my final remark was
18 my point about the provenance, data provenance, and kind
19 of applying the same rules of big data to consumers to
20 firms' handling of consumers' data.

21 MS. GEORGE: Well, thank you very much for this
22 lively discussion. We did get a couple of questions at
23 the end which we're not going to get a chance to discuss,
24 but our panelists, I think, will be around this afternoon
25 if you want to talk to them. I want to thank each of you

1 for attending and enjoy your lunch. I hope you join us
2 for the afternoon where we'll begin with a lovely
3 presentation by Latanya Sweeney. And thanks again to
4 each of our panelists for presenting.

5 (Applause.)

6 (Whereupon, a lunch recess was taken.)

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1 AFTERNOON SESSION

2 (1:22 p.m.)

3 MS. ARMSTRONG: I think we're going to get
4 started in a few minutes, everyone.

5 All right, gang, how was lunch? Okay, time to
6 find your spot without your food or beverage.

7 Great. Thank you, everyone for joining us this
8 afternoon. The afternoon session is going to be --
9 Commissioner Brill is going to give opening remarks to
10 the afternoon session and so without further ado, here is
11 Commissioner Brill, who needs no introduction.

12 (Applause.)

13 REMARKS BY COMMISSIONER JULIE BRILL

14 COMMISSIONER BRILL: Thanks, everybody. Before
15 I begin, let me just say thank you so much to Katherine,
16 to Tiffany, to Patrick Eagan-Van Meter
17 , and Katherine Worthman,
18 to all the folks at the FTC who have been working so hard
19 on this workshop. I think that the quality of the panels
20 this morning, the quality of the panels this afternoon,
21 show you how much work they put in to organizing this
22 event. So, can we just have a quick round of applause
23 for the FTC staff.

24 (Applause.)

25 COMMISSIONER BRILL: And thanks to all of you

1 who are watching by webcast and those of you who made it
2 here today.

3 Our presenters and panelists are providing us
4 with details about the current and emerging uses of big
5 data to categorize consumers, the surrounding legal
6 issues and possible best practices for big data analytics
7 providers.

8 I'd like to provide a more general, and also,
9 perhaps, a more personal perspective that makes, I hope,
10 a simple point. Providing transparency into big data
11 algorithms that categorize consumers has been done
12 before. It has put some concerns to rest and companies
13 and consumers have been better off as a result.

14 Now, as I've said on one or two other
15 occasions, those of you who have read some of my speeches
16 or perhaps attended them, I believe big data analytics
17 can bring significant benefits to consumers and to
18 society. But we must endow the big data ecosystem with
19 appropriate privacy and data security protections in
20 order to achieve these benefits.

21 Today I'd like to focus on three of the more
22 challenging issues of the intersection of big data and
23 consumer protections that pertain to this workshop. I'd
24 also like to offer some suggestions, some specific
25 suggestions, about what industry can do right now to

1 address these concerns.

2 Consumer trust is critical here and
3 transparency and accountability are key to building it.
4 Now, the first challenge involves traditional credit
5 scores derived from credit reports and alternative
6 scoring models. In this realm as in many others, past is
7 prologue.

8 The origins of the Fair Credit Reporting Act
9 have something to teach us about our current environment.
10 The FCRA was our nation's first big data law. The seeds
11 for it were planted in the growing economy after World
12 War II. Businesses formed cooperatives to enable quicker
13 and more accurate decisions about creditworthiness by
14 sharing information about consumers who were in default
15 or delinquent on loans. Over time these agencies
16 combined, paving the way for consumers to again access to
17 credit, insurance and jobs.

18 As credit bureaus increased their ability to
19 draw inferences and make correlations through ever-larger
20 databases, unease about the amount of information the
21 credit bureaus held, as well as its accuracy and use,
22 also increased. Congress passed the Fair Credit
23 Reporting Act in 1970 to address these concerns.

24 The FCRA governs the use of information to make
25 decisions about consumer credit, insurance, employment,

1 housing and other transactions initiated by consumers.
2 It covers not only credit bureaus, but also, importantly,
3 their sources and their clients.

4 The FCRA gives consumers important rights. For
5 instance, consumers are entitled to have access to their
6 data, to challenge its accuracy, to have irrelevant data
7 removed. And to be notified when they are denied credit
8 or get a loan at less than favorable rates because of
9 negative information in their files.

10 The use of credit scores has thrived under the
11 FCRA's rights of notice, access, correction, relevancy
12 and accuracy. And the FCRA has enabled the credit
13 reporting enterprise to serve a purpose useful not only
14 to the credit reporting agencies and their clients, but
15 also to consumers.

16 The credit scores that first emerged from
17 analysis of consumers' credit files broadened access to
18 credit and made determinations of a particular consumer's
19 worthiness more efficient and more objective, than the
20 case was with prior, more subjective, determinations.

21 Now, as scoring models began to proliferate and
22 enter into new types of decisions, including employment,
23 insurance and mortgage lending, consumers and regulators
24 grew concerned about what exactly was going on within
25 these models. Some of the most important questions were

1 whether credit-related scores were using variables that
2 act as proxies for race, ethnicity, age and other
3 protected categories.

4 In 2003 Congress directed the Federal Trade
5 Commission and the Federal Reserve to study these
6 questions in the context of credit-based insurance scores
7 and traditional credit scores. After extensive and
8 rigorous studies, both agencies found that the scores
9 they examined largely did not serve as proxies for race
10 or ethnicity. The FTC and Federal Reserve reports shed a
11 lot of light on traditional credit scores and assuaged
12 some important concerns, which was good for everyone
13 involved -- consumers, credit bureaus, and credit score
14 users.

15 Now, let's fast forward to today. We're now
16 seeing a proliferation of other types of scores being
17 used to make FCRA covered eligibility determinations.
18 While these scores are subject -- or, many of them are
19 subject to the same obligations of access, accuracy,
20 security and other requirements imposed by the FCRA, they
21 haven't yet been subject to the same kind of scrutiny
22 that Congress and the Federal agencies brought to bear on
23 traditional credit scores.

24 The use of new sources of information,
25 including information that goes beyond traditional credit

1 files to score consumers, raises fresh questions about
2 whether these alternate scores may have disparate impacts
3 along racial, ethnic or other lines that the law protects
4 or that should be addressed.

5 Those questions are likely to linger and grow
6 more urgent unless and until the companies that develop
7 these alternate scores go further to demonstrate that
8 their models do not contain racial, ethnic, or other
9 prohibited biases. These companies may learn that their
10 models have unforeseen inappropriate impacts on certain
11 populations. Or they might simply find their algorithms
12 should eliminate or demote the importance of certain type
13 of data, because their predictive value is questionable,
14 as FICO recently discovered with respect to paid off
15 collection agency accounts and medical collections.

16 Just as we did a decade ago, the FTC and other
17 appropriate Federal agencies should once again devote
18 serious resources to studying the real world impact of
19 alternate scoring models.

20 But industries shouldn't wait for Federal
21 agencies or for Congress, for that matter, to get
22 involved to review their own scoring models. Companies
23 can begin this work right now and provide us all with
24 greater insight into, and greater assurances about, their
25 models.

1 The second big data challenge I'd like to
2 discuss comes from the unregulated world of data brokers.
3 As outlined in the Commission's recent report, as was
4 discussed this morning, data brokers' profiles combine
5 massive amounts of data from online and offline sources
6 into profiles about nearly all of us. Data brokers'
7 clients use these profiles for purposes that range from
8 marketing to helping companies determine whether, and on
9 what terms, they should do business with us as individual
10 consumers.

11 Now, the main data broker issue that I'd like
12 to highlight today concerns data broker segments that
13 track sensitive characteristics, including race,
14 religion, ethnicity, sexual orientation, income,
15 children, and health conditions.

16 As I noted, when the FTC released its landmark
17 report on data brokers, I see a clear potential for these
18 profiles, ethnic second city struggler or urban
19 scrambler, to harm low-income and other vulnerable
20 consumers.

21 In an ideal world, a data broker's products
22 that identify consumers who traditionally have been
23 under-served by the banking community can be used to help
24 make these consumers aware of useful opportunities for
25 credit and other services.

1 However, these same products could be used to
2 make these consumers more vulnerable to high interest
3 payday loans and other products that might lead to
4 further economic distress.

5 It all depends on how these products are
6 actually used. Importantly, our recent data broker
7 report did not attempt to analyze the harms that could
8 potentially come from the uses of consumer segmentation
9 of poor or minority communities.

10 Now, one of the reasons I support legislation
11 to create greater transparency and accountability for
12 data brokers, as well as their sources and customers, is
13 so we can all begin to understand how these profiles are
14 being used, in fact, and whether and under what
15 circumstances they are harming vulnerable populations.

16 In the meantime, the data broker industry
17 should take stronger pro-active steps right now to
18 address the potential impact of their products that
19 profile consumers by race, ethnicity, or other sensitive
20 characteristics or that are proxies for such sensitive
21 classifications.

22 Here's what I'd like to see data brokers do.
23 They should find out how their clients are using these
24 products. They should tell the rest of us what they
25 learn about their actual uses. They should take steps to

1 insure any inappropriate uses cease immediately and they
2 should develop systems to protect against such
3 inappropriate uses in the future.

4 Now, the third challenge I want to mention
5 relates to companies that use their own data and analyze
6 their own data about their customers.

7 Companies, understandably, are eager to
8 determine what makes their customers happy and how they
9 can more efficiently service these customers. As they
10 dive into their own treasure trove of customer data in
11 order to offer perks or better deals to loyal customers,
12 companies may also find that these common practices
13 disadvantage certain groups of individuals, thereby, in
14 the words of the White House's big data recent report,
15 exacerbating existing socio-economic disparities.

16 Back in January, the Harvard Business Review
17 asked companies to think deeply about where value-added
18 personalization and segmentation ends and harmful
19 discrimination begins.

20 Now, I want to emphasize that all of these
21 industry players, traditional credit reporting agencies
22 and their newfangled progeny using alternate scoring
23 models, data brokers and the companies that use their
24 products, and companies engaged in analysis of their own
25 customer data, all of these players can take steps right

1 now to address concerns about the potential
2 discriminatory impact of their use of algorithms.

3 I'm hopeful that the same reservoirs of data
4 that create the concerns I outlined will also lead to
5 ways to get them under control. I encourage all members
6 of industry to look for ways that the data in their hands
7 could be used to identify disparate treatment along
8 racial, ethnic, gender or other inappropriate lines, and
9 to correct such treatment to the extent it exists.

10 Thank you very much.

11 (Applause.)

12 MS. ARMSTRONG: Thank you very much,
13 Commissioner Brill.

14 Now, the next part of our afternoon agenda,
15 before we get to the next panel, is going to be a
16 presentation, Digging Into the Data, and I'd like to
17 introduce LaTanya Sweeney, who's been the Chief
18 Technologist at the FTC, and Jinyan Zang, a research
19 fellow in technology and data governance. So, I'll leave
20 you with the clicker.

21 (Applause.)

22 PRESENTATION: DIGGING INTO THE DATA

23 MS. SWEENEY: So it's great to be here. My
24 name got mentioned a couple of times, so I feel like I
25 don't need any other introduction. But I do want to

1 thank Tiffany and Katherine and Katherine and Patrick and
2 Maneesha and DPIP for organizing this and for allowing us
3 this opportunity to present our work. Assuming I can get
4 the clicker to work, because after all I'm the
5 technologist, right?

6 So one of the things I wanted to also let you
7 know is we started a summer research program under the
8 guidance and leadership of Chairwoman Ramirez, who
9 you met this morning. The idea was to bring in some of
10 the best and brightest students and have them do research
11 during the summer on areas of interest to the FTC.

12 Today we're going to report on one such
13 project, but let me -- and we worked as a team, so all of
14 the fellows were pretty -- kind of contributed to all of
15 the efforts, but Jin and I primarily did the one that
16 we're going to talk about today.

17 Krysta and Jim couldn't be here, but Paul is
18 here, I'll just have him stand up. And the work that's
19 coming out from the other fellows will be coming over the
20 next weeks.

21 So, the Pittsburgh Courier was once the
22 country's most widely-circulated black newspaper, it had
23 a circulation of about 200,000. If you worked for the
24 Courier or if you were to interview their staff back in
25 1911, they would say that -- your clicker doesn't work --

1 they would say that when an ad appeared in their
2 newspaper they would review that ad. They had to review
3 that ad because they didn't want to run the risk of
4 alienating, isolating, or insulting the audience that
5 they served.

6 Today, the Pittsburgh Courier -- the clicker
7 still doesn't work -- is an online website and their ads
8 are delivered through an online network for which no
9 staff member actually reviews the ad. Instead, it's a
10 big data analytic engine that delivers their ad.

11 Now, we all know the promise and we've heard a
12 lot about the advantages of big data analytics and online
13 advertising is no exception. It's not that you want just
14 any old ad showing up anywhere, you want the ads
15 organized so that the fisherman sees the fisherman ads
16 and the young mother sees the baby products. And so
17 that's the promise.

18 But in order to deliver that, there's a lot
19 that happened to get that Macy's ad on that Pittsburgh
20 Courier page. There are a lot of parties and a lot of
21 different ways that can happen. So let me sort of just
22 blow it up and introduce some of the ways.

23 So there's groups that will help you put
24 together your ad campaign and your ad copy, help you find
25 platforms on which to sell it. There are data brokers

1 that are involved in taking the outside data -- is it the
2 battery or is just I don't know how to push the button?

3 (Laughter.)

4 MS. SWEENEY: Data brokers taking outside data,
5 bringing it into the online network, figuring out what it
6 is to offer or what kind of offer, which ad would be the
7 right one to target directly to you, and make that
8 connection from end to end through that kind of network.
9 And so that's normal and called targeted advertising.

10 But we're not going to talk about targeted
11 advertising right now. Let's talk about something
12 simpler, where it's only one party that's going to go
13 from end to end, such as the Google network.

14 Google delivers more than 30 billion ads a day.
15 And every ad is delivered in the time it takes to load a
16 web page. That's -- I'm a computer scientist, that is
17 awesome. That's really awesome. How do they do this?
18 Well, we're not going to get into the specifics and I'm
19 not sure everyone actually knows the specifics outside of
20 Google, but we do know that there are billions of ads on
21 one side. And what an ad bid is, is basically the copy,
22 the ad copy, the key words of the audience that they
23 would like to show that ad to, and how much money they'll
24 pay either to get that ad put in front of the audience or
25 for someone to click on it.

1 On the other side are these publishers, who
2 will basically take an ad. And so Google gets to make
3 the decision as to which ad is going to show up when.

4 We're very interested in how Google goes about
5 doing that. Not so much about ripping open that cloud,
6 that blue cloud, but understanding what effects might be
7 on the outside.

8 So one of the things we did was we turned to
9 Mixrank. Mixrank is a service whose whole business is
10 about capturing online ads. So they survey the internet
11 constantly, record every ad they encounter, where they
12 encountered it, the data that was encountered, and so
13 then you can look at the data through the eyes of the
14 publishing side or through the advertisers. So this is
15 an example.

16 One of the things they do is they get rid of
17 behavioral effects and re-targeting effects. So this is
18 nice for our study, because now we're looking at it with
19 the assumption that that blue cloud doesn't know anything
20 more about you than it would know about anyone else. And
21 in those circumstances, how does the blue cloud perform.

22 So we found this website, Omega Psi Phi. Now,
23 Omega Psi Phi had its 100th anniversary in 2011, set up a
24 special domain just for the site. It's a fraternity that
25 is very popular in the United States among black men in

1 colleges. It supports many outstanding black men among
2 its members, including Congressman Clyburn, Bill Cosby,
3 Shaquille O'Neal.

4 And we became interested in what kind of
5 advertisements showed up on that site. Well, there are
6 lots of ads about graduate degree programs, which, of
7 course, seems incredibly appropriate, given that this is
8 an undergraduate fraternity -- and a clicker that doesn't
9 work. What is it with this?

10 (Laughter.)

11 MS. SWEENEY: There are also advertisements
12 about, you know, luxury vacations and other kinds of
13 opportunities like that. And then there are also these
14 kinds of advertisements, such as this one, "Click here to
15 view your arrest record now."

16 Now, there has been much said about Instant
17 Checkmate and this is an Instant Checkmate ad. I did
18 earlier work about the suggestive nature of arrest record
19 ads around Instant Checkmate, but I think it's very clear
20 to see that this actual ad is not showing up the way it
21 regularly showed up. It actually shows up with flashing
22 colors, so it has kind of a neon effect. But flashing
23 your arrest record would be a presumption that this
24 particular audience would not appreciate.

25 It wasn't the only ad, though, that made that

1 kind of presumption. There were also ads for a criminal
2 lawyer and there were ads for credit cards.

3 Now, it turns out the financial industry is the
4 number one marketer online. So they're the number one
5 industry that's advertising online. And given what we
6 had just seen of Omega Psi Phi, we became very interested
7 in what kind of credit card ad is that and what are
8 credit card ad experiences. I hope you have better luck
9 with the clicker.

10 MR. ZANG: All right. So, going more generally
11 from the Omega Psi Phi anecdote, we first started looking
12 for word lists of quality cards versus ones that are more
13 harshly criticized online.

14 So, here you can see a list of the top 25 most
15 harshly criticized cards or the most highly praised cards
16 that we were able to find. And for Omega Psi Phi, they
17 actually had two of the ads from the harshly criticized
18 list show up on their site, including First Premier Card
19 and the Centennial Card. None of the ads from the highly
20 praised cards list actually showed up on their site.
21 And, in fact, for the highly praised cards list, it's not
22 necessarily those cards are all just high credit score,
23 really luxury cards. In fact, you had secure cards that
24 were highly praised as well, like the Capital One secure
25 card.

1 So, but digging back into the comparing of the
2 two cards, what we saw was if you looked at the most
3 popular ad that ran for a First Premier card, which is
4 one of the most often criticized cards, if you go online
5 and compare that to the most popular ad that was run by
6 American Express for their blue card, the sites that
7 appear that those card ads appeared on do look very
8 different.

9 And one theme that quickly jumps out at you,
10 especially for the American Express blue card is, around
11 higher education, where you had sites such as
12 Harvardmagazine.com or Yalealumnimagazine.com or, like,
13 the Heismanwinners.com as sites that American Express is
14 advertising on.

15 On the other hand, for First Premier's card
16 there didn't seem to be as much of a cohesive theme that
17 we picked up.

18 MS. SWEENEY: So we wanted to dig further.
19 Like, what is the nature of these cards, where are they
20 appearing generally, and is it somehow related perhaps to
21 the popularity of the website.

22 So if you think about popularity of websites,
23 there are a few websites that are highly popular, almost
24 everyone goes to, they're on the top of everyone's top
25 ten list. And then the popularity of the website drops

1 as you go further out.

2 Alexa is a company that ranks the traffic to
3 and from domains and so we used them to rank all of the
4 publishers of all of the credit card ads' deliveries that
5 were made of the praised cards and the criticized cards.
6 And what we learned was that the criticized cards
7 appeared completely across the entire spectrum in
8 increasing order as the popularity of the domain drops.
9 So it's a curve that's going this way. And in every
10 segment of the popularity zones, there are, in fact,
11 credit card ads for the criticized cards.

12 The highest number, though, were in those ads
13 whose popularity ranks were above a billion. Now, to be
14 above a billion, you probably aren't getting much
15 traffic, that would be the issue with respect to their
16 popularity. Those ads that are close to the left are
17 highly popular, those are very curated, and there's a lot
18 of information that exists about the audience. And you
19 could actually look up on services with Quantcast to find
20 out the demographic make-up of those websites. But when
21 you're way out in the billions and millions, that kind of
22 information doesn't exist.

23 The other thing to note, though, is where were
24 the praised cards? They didn't follow the same pattern.
25 Instead, they were heavily generated in the middle around

1 the 100,000 to the one billion.

2 So these ads are showing up on different
3 popularity, on websites and domains with different kinds
4 of popularity profiles.

5 MR. ZANG: And another perspective that we took
6 to look at the type of sites that these card ads were
7 running on was from the perspective of understanding that
8 different websites do attract different types of
9 audiences and that there are websites out there that are
10 more exclusive to an audience of one demographic group
11 than other demographic groups.

12 So we took the approach of analyzing Comscore's
13 data on the browsing behavior of 46,000 American
14 households in 2013 and looked through the four million
15 websites those households go to, to look for sites that
16 are more commonly visited by households of certain
17 demographic groups.

18 And so, for example, if we took a racial lens
19 to demographics, you can -- we found that for Latino
20 Americans they're more likely to go to sites like
21 Univision or Tarango or Musica.com. For African American
22 households they went to sites like Worldstarhiphop or
23 Footlocker.com.

24 Now, in this case, it doesn't necessarily mean
25 that only African Americans go to Footlocker.com.

1 Footlocker.com could have lots of other visitors from
2 other racial groups as well, but African American
3 households are much more likely to go to Footlocker.com.

4 And so we looked at exclusivity from the lens
5 of race, from age, from income, from the level of
6 education in the household and also whether the household
7 had children or not. And we are able to find for each of
8 those different lenses, sites that were exclusive to each
9 of those groups.

10 And this raises a question for us of if there
11 are sites that are out there that are more exclusive to
12 certain groups, what is the advertising experience like
13 on those sites. And could there be the potential for
14 disparate impact if -- depending on the type of ads that
15 are shown or the type of ads that are actually not shown
16 on those sites.

17 MS. SWEENEY: So, one of the things that we
18 learned was that these groups are appearing almost evenly
19 across the entire popularity of these domains. That
20 means that no matter which ad campaign you ran, whether
21 one you were trying to focus on popular domains or less
22 popular domains, you could easily encounter one of these
23 domains for which there was an exclusive audience,
24 because, in fact, they appeared in all the domains.

25 So, what we then became interested in was to

1 what extent could we predict whether or not the ad would
2 receive or were there sites in the comScore data that
3 should have received these credit card ads and were those
4 sites part of these exclusive groups.

5 And we found that it's true, that around race
6 and income and age, there were differences. And, in
7 fact, there were praised ads. And these praised ads, for
8 example, for Asians, we saw Capital One secure card and
9 Capital One and CitiBank and Discover finding domains for
10 which Asians -- were more exclusive to Asians. And you
11 couldn't tell by the name or the key word of the page,
12 the domains are names like Dealstobuy.com or
13 Visajourney.com.

14 Discover did a very good job using
15 Seekingalpha.com to target people who are more -- whose
16 income is \$100K or more. That's an exclusive audience at
17 Seekingalpha.com and it's a very popular site.

18 And then we also found examples in age ranges.
19 Discover, with ages 18 to 20 and Capital One secure card
20 found some domains that were somewhat exclusive to ages
21 25 to 29 or ages 65 plus.

22 So, domains with exclusive audiences do exist
23 and ads are not exempt from being delivered to those
24 sites. So the lack of ads or too much of another ad,
25 could lead to a disparate impact. And demographics

1 could, therefore, sort of infer what kind of advertising
2 experience might you have.

3 We're going to stop here. If you want more
4 information about the work, we'll have a blog post later
5 with some of the details and a paper to follow right
6 after that.

7 I did want to leave the panel that's coming up
8 next with three questions from this work. One of them is
9 that by subscribing to an online ad network a publisher
10 may not have an opportunity to review ads anymore and if
11 there is a problem, what are the publisher's rights and
12 responsibilities?

13 Another question that comes from this is when
14 we look at Omega Psi Phi. What are the sufficient and
15 necessary circumstances for a community to experience
16 adverse impact in this setting?

17 And the last question is that the kind of
18 audience exclusivity measure that we used to find these
19 audiences that had that type of exclusive nature to the
20 audience is something that could actually be used inside
21 of the big data engine in that same fraction of a second,
22 to realize that this ad probably shouldn't go to this
23 site at this time.

24 If that's so, and it's that easy to do, should
25 or how might a big data analytic engine be required to

1 use it or an equivalent remedy?

2 So to find out more about the work, check out
3 our Tech@FTC blog. Thank you.

4 (Applause.)

5 MS. WORTHMAN: Good afternoon. My name is
6 Katie Worthman, I'm an attorney in the Division of
7 Financial Practices here at the FTC and I am co-
8 moderating the third panel, along with my colleague,
9 Patrick Eagan-Van Meter, who is a program specialist,
10 also in the Division of Financial Practices.

11 Panel 3 is titled Surveying the Legal
12 Landscape. And today we are going to look at the various
13 anti-discrimination and consumer protection laws that
14 impact big data.

15 Let me first quickly introduce the panel. To
16 my immediate left is Leonard Chanin, who is currently a
17 partner in the law firm of Morrison Forester, who in a
18 previous life also was head of regulations at the Federal
19 Reserve and at the Consumer Financial Protection Bureau.

20 Then there is Carol Miaskoff, who is in the
21 Office of Legal Counsel at the Equal Employment
22 Opportunity Commission.

23 Montserrat Miller, who is a partner in the
24 Privacy and Consumer Regulatory, Immigration and
25 Government Affairs Practice Groups, at Arnall Golden

1 Gregory.

2 And Lee Peeler, who is President and CEO of the
3 Advertising Self-Regulatory Council and Executive Vice
4 President National Advertising Self-Regulation Council of
5 Better Business Bureaus.

6 And then last, but definitely not least, is
7 Peter Swire, who is a Professor of Law and Ethics at the
8 Georgia Institute of Technology, as well as Senior Fellow
9 at the Future of Privacy Forum and the Center for
10 American Progress.

11 And with that, I will ask Patrick to open up
12 the panel with the first question.

13 PANEL 3: SURVEYING THE LEGAL LANDSCAPE

14 MR. EAGAN-VAN METER: So, Panel 2 kind of
15 teased us a little bit with the laws that might apply to
16 the big data space, so I wanted to ask all of you what
17 you think the Federal laws that touch on the collection
18 and use of big data are.

19 MS. WORTHMAN: Leonard?

20 MR. CHANIN: So I was asked to give a little
21 background on the Equal Credit Opportunity Act and
22 Regulation B, just to kind of do some level setting in
23 terms of how that law may apply to big data marketing and
24 those sort of things. So I'll spend just a couple of
25 minutes talking about that.

1 So the Equal Credit Opportunity Act
2 implemented by Regulation B, the Federal Reserve Board
3 administered that regulation for many years and it was
4 recently, or a couple years ago, transferred to the CFPB.
5 So, interestingly enough, the Equal Credit Opportunity
6 Act doesn't apply to marketing activities, Regulation B
7 does to a limited extent. And the reason is the law says
8 it's illegal to discriminate against an applicant in
9 connection with a credit transaction. An applicant is
10 defined as someone who has applied for credit. So if you
11 have not applied for credit, technically speaking, the
12 law does not apply to you -- that is, the Equal Credit
13 Opportunity Act does not apply to pre-application
14 activities.

15 The Federal Reserve Board, though, many years
16 ago applied Regulation B to certain activities at the
17 pre-application stage, but it's pretty narrow or focused,
18 if you will. So, first of all, the law says you cannot
19 discourage a person from applying for credit on a
20 prohibited basis. And that means something like you
21 cannot make statements to a person, you can't use
22 advertisements, radio, newspapers, and so forth that
23 would put forth symbols or tags that would discourage a
24 reasonable person from applying for credit.

25 The second way that Regulation B might cover

1 marketing activities is if you're an existing account
2 holder. So there you have a credit transaction with the
3 lender and the lender cannot make statements that would
4 discourage you from using your credit or provide
5 different terms to you, since you are, indeed, someone
6 part of a credit transaction.

7 So, generally speaking, Regulation B applies to
8 transactions or applies to marketing in those relatively
9 focused ways. But it's not a new issue that we're
10 talking about in terms of marketing. In fact, the
11 Federal Reserve in 1985 looked at marketing activities,
12 decided at that time not to expand the regulation scope
13 to cover marketing activities. And again looked in 1998,
14 when it was reviewing Regulation B and solicited comments
15 on whether pre-screening activities should be covered by
16 Regulation B.

17 In 1999, the Federal Reserve Board decided that
18 it was not appropriate to apply Regulation B in its full
19 context to pre-application activities, marketing
20 activities, because it did not have evidence that
21 suggested that lenders were using, in any significant
22 way, prohibited bases for marketing. The Fed also said,
23 though, it had anecdotal evidence suggesting that some
24 lenders were using age, that some were using geographical
25 information in terms of marketing activities, but

1 balanced that anecdotal information against the benefits
2 of marketing. That is, that pre-screening, in
3 particular, makes credit available to individuals. There
4 was evidence that the Fed cited that said that allowing
5 lenders to engage in pre-screening without coverage by
6 Reg. B could make credit available to more individuals.

7 The Federal Reserve also noted that, of course,
8 lenders could use information to discourage people from a
9 fine, could use information to provide products to some
10 areas and not to, if you will, disadvantage products.

11 So, in 2003 the Federal Reserve Board actually
12 adopted a rule dealing with pre-screening marketing
13 activities coming out of a 1999 proposal. That rule is
14 still in place today. It basically requires creditors to
15 retain information about pre-screening activities, that
16 is, activities where creditor use is governed by the Fair
17 Credit Reporting Act, uses credit report information, and
18 a creditor must retain the information used to market --
19 that is, the criteria.

20 So, today, and since about 2004, if a creditor
21 uses information -- race, ethnicity, age, gender, et
22 cetera -- to engage in pre-screening it must, under the
23 law, retain that information. The Fed, at the time of
24 adopting this rule, said that enforcement agencies could
25 use this information to determine whether or not pre-

1 screening was being engaged in by lenders in an
2 inappropriate fashion. Whether that data has been
3 provided by the Fed or the CFPB in the last few years is
4 questionable, but there is some law in place now that
5 will at least arguably provide some more data to various
6 agencies, in terms of pre-screening and marketing
7 activities.

8 So that's a very long answer to your short
9 question.

10 MS. WORTHMAN: But one thing, also, is that the
11 Equal Credit Opportunity Act applies in what space?

12 MR. CHANIN: So the Equal Opportunity Act
13 applies only to credit transactions, but it applies quite
14 broadly, that is, to all credit transactions; consumer
15 credit, business credit, credit to corporations, to sole
16 proprietorships, partnerships and the like. It's not
17 limited to consumer transactions. It is quite broad in
18 its applicability.

19 There are obviously, in addition to the anti-
20 discrimination provisions, rules dealing with adverse
21 action notices if you decline credit to people, you have
22 to give them a notice, and those sort of things. So it's
23 quite broad in terms of its scope.

24 MS. WORTHMAN: And, Carol, in the Title 7
25 context?

1 MS. MIASKOFF: Right, right. In the context of
2 the Civil Rights Act of 1964, as well as the other
3 Federal EEO laws, the Americans With Disabilities Act,
4 the Age Discrimination and Employment Act, and the
5 Genetic Information Non-Discrimination Act, not to miss
6 that, we have really very settled law. I mean, it's the
7 50th anniversary of the Civil Rights Act this year, but
8 settled law with some basic principles that, I think, can
9 definitely be translated into the big data space.

10 Now, how do these employment and non-
11 discrimination laws sort of reach over? How does
12 employment meld with the big data? I think it does in
13 the spaces of recruitment, clearly, for the kind of
14 advertising issues we've been seeing discussed here. And
15 in areas of screening people for jobs once they have been
16 recruited and making that ultimate selection decision.
17 There's a real potential here, I think, to gather
18 information about successful employees and then turn
19 around and use that to screen people for employment.

20 With the screening piece, I think the issue
21 really is about what prejudices are built into the data
22 and, therefore, would be built into any rules deduced
23 from the data. And, therefore, be used to select people
24 who meet those same rules. So, would it exacerbate,
25 perpetuate, past discrimination? I think that's the big

1 concern.

2 In recruitment it's the same issue around
3 advertising that we've seen in the commercial space. And
4 I know -- you know, think about LinkedIn and all the jobs
5 that may be referred to you there. And, you know, you
6 always wonder, you know, who's getting which jobs, are
7 they equitably distributed or not, or are they targeted?

8 So, I think that's the big picture. In terms
9 of the law I just want to make a few quick points.

10 It's been interesting to me, because everyone's
11 been talking about disparate impact and adverse impact a
12 lot. In the employment space, those are very precise
13 legal terms. And there is a cause of action for
14 disparate impact and I would say that that's the one,
15 frankly, that's most suited to big data, because what
16 that's about is taking a neutral, i.e., like, race
17 neutral, gender neutral, et cetera, term, that
18 nonetheless disproportionately excludes members of the
19 protected group. And -- and this is the critical piece
20 here -- and is not job-related consistent with business
21 necessity.

22 Now, in terms of big data I think this is the
23 rub, this is really what's very fascinating, is that the
24 first step is to show, is to look at what is the tool.
25 Now, you know, this could apply to recruitment or to

1 selection, perhaps more to selection.

2 What is the tool, does it cause a disparate
3 impact, and once you get there, is -- you know, just
4 because it causes disparate impact, doesn't make it
5 illegal discrimination under the employment laws. It's
6 only illegal if it does not predict, accurately predict,
7 success in the job. Okay?

8 So this raises all kinds of fascinating issues
9 with big data analytics, because, indeed, if you do
10 possibly have prejudices and prejudice is built into the
11 data, something might be validated as predicting success
12 in the job, but it might just be predicting that, you
13 know, white guys who went to Yale do well in this job.

14 So, you know, there's going to be a lot of
15 interesting, I think, thought that needs to be done and
16 technology work, really, around understanding how to
17 validate these kind of concerns.

18 MS. WORTHMAN: Montserrat, with respect to the
19 Fair Credit Reporting Act?

20 MS. MILLER: Sure. So, I am going to talk a
21 little bit about the Fair Credit Reporting Act and try to
22 weave that into big data and how certain reports are used
23 in that context.

24 So, FCRA, enacted in the early 1970s, a
25 consumer friendly statute. And what it seeks to regulate

1 or who it seeks to regulate are consumer reporting
2 agencies, so credit bureaus or background screening
3 companies. And it's very specific in what it seeks to
4 regulate and how it seeks to regulate it. So that
5 consumer reporting agencies operate in an environment in
6 which they -- with respect to confidentiality, accuracy
7 and then also the legitimate use and permissible use of
8 data.

9 And when you're talking about the FCRA or the
10 Fair Credit Reporting Act, we're looking at consumer
11 reports, consumer reporting agencies, users of the
12 consumer reports and also furnishers of the data for the
13 consumer reporting agencies. So it's an ecosystem in
14 which these companies operate under the Fair Credit
15 Reporting Act.

16 With respect to the reports, themselves -- and
17 this is where you begin to get into, obviously, the data,
18 the reports could include credit, they could include
19 criminal history information, obviously, that's something
20 that comes up with employment, in both of those they
21 could include drug testing information, employment
22 education verification, public records information.

23 So these are reports that are put together by
24 consumer reporting agencies provided to, for instance,
25 employers, landlords, and others, all within the confines

1 of the Fair Credit Reporting Act. And the information
2 contained within those reports, the data contained within
3 those reports, goes to credit-worthiness, standing,
4 capacity, and it also goes to character, general
5 reputation or mode of living.

6 And Commissioner Brill covered some of these
7 points already, so I won't belabor them, but as she
8 mentioned, they're certainly looking at the use of that
9 data for credit or insurance or employment purposes, or
10 other purposes. But all purposes which are defined and
11 regulated under the Fair Credit Reporting Act are
12 permissible purposes.

13 So, I would say with respect to the Fair Credit
14 Reporting Act, you're looking at, as I said, permissible
15 purposes, due diligence of end users, who are going to be
16 looking at the data, consumer reporting agencies must
17 operate with maximum possible accuracy, and there's
18 always, and most important for consumers, whether it's
19 for employment or tenancy or credit or insurance, other
20 purposes, there's always the right to essentially appeal
21 and challenge the accuracy and completeness of any
22 consumer report.

23 FCRA, over the years, has not operated on its
24 own. We've certainly seen the states coming into this
25 space and especially, I think, aggressively over the last

1 few years when you talk about the potential
2 discriminatory impact of the data that's in those
3 reports, and, really, with respect to credit and criminal
4 history. So, you have not only the FCRA, which is
5 enforced by the FTC and the CFPB, and also there are
6 private rights of action, but you have the state analogs,
7 which are essentially their own mini FCRA's and you have
8 California, Colorado, Maine, Minnesota, New Mexico, New
9 York, Oklahoma, Vermont and Washington State.

10 So you can see there are a lot of people, a lot
11 of different entities, Government entities, enforcers,
12 that are operating in the space of using this big data
13 with respect to the permissible purposes.

14 And then you also have other states, which have
15 gone more -- in a more limited, but important, area and
16 consider whether the use of credit for, say, employment
17 or tenancy might have -- that in certain settings the use
18 of credit could have -- be considered an unlawful or
19 discriminatory practice. And the same applies with
20 criminal history information.

21 So, certainly, there are examples of states who
22 are very active in this space of data, big data, and how
23 it's used in these reports, in seeking to protect the
24 community and I think certainly some individuals in
25 certain communities.

1 MS. WORTHMAN: Thank you. And, Lee, could you
2 speak a little bit about section five?

3 MR. PEELER: Sure, I would love to. And,
4 although, I do think I was sort of targeted as the legal
5 historian on this panel.

6 And, you know, I do want to also just commend
7 the FTC's leadership on this. You know, data is now the
8 economic lubricant of a lot of our economy. And looking
9 at this issue is in the finest tradition of the Federal
10 Trade Commission -- in fact, if you're looking for
11 historical analogies, in the 1960s the FTC launched a
12 ground-breaking review of inner city retailers' marketing
13 practices and that led, under the Federal Trade
14 Commission Act, which I'll talk about in two seconds, to
15 a whole wave of initiatives that really changed a lot of
16 what we traditionally thought of about credit practices
17 and debt collection practices and merchandising.

18 So, you know, I think this is really, again, in
19 the greatest tradition of the Commission.

20 I do want to go back to some remarks that were
21 made this morning, though, and say I think you have to --
22 you can't just look at the application of the FTC Act
23 broadly on big data. I think the remarks that were made
24 this morning really say you have to look at how -- at
25 where big data is being used and how it's being applied.

1 And so one critical distinction that I think has been
2 talked about a little, but I think is really important
3 for what I'm about to talk about, is the distinction
4 between decision making, granting or denying credit,
5 granting or denying a job, and advertising and marketing.
6 And, you know, the decision making for credit,
7 longstanding prohibitions, going back to 1974, on using,
8 you know, marital status or race in the decision making.

9 In advertising the traditions are the opposite.
10 Advertising is necessarily about targeting your products
11 to markets. You can just look at cosmetic ads, if you
12 look at ads for shavers, if you look at ads for music,
13 for books, all of those ads you're going to find
14 targeted. And probably, you know, the best example of
15 ongoing massive targeting is in selling political
16 candidates right now.

17 So how does the FTC Act apply to those areas.
18 And, again, my background is advertising, so I want to
19 focus on advertising in talking about the application of
20 the FTC Act.

21 The first piece of the FTC Act is deception.
22 Whether an act or practice would mislead a consumer
23 acting reasonably under the circumstances. And there
24 were sort of two basic applications there. One is well
25 established legal principle, if you're narrowly targeting

1 an audience, you're responsible for the reasonable
2 interpretation that audience would have. So if you're,
3 you know, targeting your ads to cancer patients in a
4 well-known FTC case, you are liable for what the
5 interpretation of that ad would be and what information
6 that consumer would need, if you're narrowly targeting.

7 The other example that I think will be
8 important as the FTC goes down the road is, you know,
9 data brokers are responsible for the accuracy of what
10 they tell consumers and tell marketers they're providing
11 them, so they're responsible for the accuracy of the
12 representations they make about their database.

13 The second core aspect of FTC jurisdiction is
14 unfairness. There is a long history of unfairness that
15 led to its codification in 1994, but it's a -- you know,
16 it's a provision that's been in the Federal Trade
17 Commission Act since consumer protection authority was
18 created in 1934.

19 The elements of an unfair practice under the
20 1994 codification are that the practice is likely to
21 cause substantial consumer injury. And that that injury
22 is not reasonably avoidable by consumers and on that
23 particular part of the analysis you would need to look at
24 whether the ad is targeted to a specific group, but also
25 what's the consumer group's access to alternative

1 products, how easily can the group go on and find
2 alternative products at better prices or at better terms?

3 Even if you met that analysis for advertising,
4 your next -- the next challenge is to show that that
5 harm, that net harm, is not outweighed by benefits to
6 consumers or competition.

7 And again, you know, a flat ban on use of, for
8 example, gender in advertising would probably fail under
9 that approach because, you know, take, for example, an
10 entrepreneur wants to open a women's shoe store. They
11 will be targeting their ads based on sex and gender.

12 Probably -- and then the big issue for legal
13 analysis under section five is what extent has well
14 established public policy had. And we have a very well
15 established public policy in the United States of not
16 treating people differently. The statute that created
17 the codification is quite clear, that you can use public
18 policy in weighing the costs and benefits, but it cannot
19 be the primary basis for the conclusion that the practice
20 causes net consumer injury.

21 And then a last -- two last pieces of the FTC's
22 authority that I think are really important for the
23 discussion today, is what you're doing right now, which
24 is the ability to use your 6(b) authority to collect
25 information, issue reports and inform the public about

1 what's really going on in the marketplace is invaluable.

2 And the last is not a specific provision of the
3 Federal Trade Commission Act, but the FTC's programs of
4 educating consumers. And as Commissioner Brill said
5 earlier today, really encouraging industry to step
6 forward and educate consumers themselves.

7 And then the very last point I want to make is
8 I thought Commissioner Brill and Montserrat did a great
9 job summarizing the Fair Credit Reporting Act. But
10 because I'm an industry self-regulator I -- when I first
11 got to the FTC I took the Fair Credit Reporting Act as it
12 existed then and you could almost -- it was almost
13 verbatim from a pretty well established set of industry
14 self-regulatory principles that had pre-existed the Act
15 by several years.

16 And the only lesson I -- the important lesson,
17 I think, to learn from that is that by looking at what
18 the industry is doing on a self-regulatory basis, you can
19 come up with workable -- you're more likely to come up
20 with workable solutions to issues, than if you just try
21 to create it yourself.

22 So that's my summary.

23 MS. WORTHMAN: I'd like to turn a little bit,
24 Peter, to an example that was used this morning on Panel
25 1. And it was the Maserati example, where apparently

1 Maserati, the sports car, the example that was used by
2 Mallory Duncan was that the dealership has information
3 that the Maserati is most likely to be sold to this list
4 of people. There's a 30 percent chance that people who
5 get any type of offer will come in and purchase the
6 Maserati. And the list happens to be 95 percent male.

7 So, the question is, does that -- if you send a
8 flyer advertising a free test drive to this list that's
9 95 percent male, does that implicate the ECOA, fair
10 marketing purposes? Does it matter if it's Maserati
11 Finance Company?

12 And I know that you've released a paper
13 recently on fair marketing.

14 MR. SWIRE: Okay. Thanks. So I'll briefly say
15 that and then make a couple of other points that were in
16 the paper perhaps.

17 One of the things in the disparate impact test,
18 which is the way the Equal Credit Opportunity Act has
19 been applied, is it's facially neutral, but then if there
20 is a different impact on the protected class, is there a
21 business necessity and is there any less restrictive way
22 to do it.

23 And you can certainly imagine where the act
24 applies. That advertising to women's shoes or for the
25 Maserati, if the facts are there, there'd be an argument

1 that there's business necessity and then there'd be a
2 question of is there less restrictive alternatives.

3 So that's the way I think it's been done in the
4 fair lending context. I would like to, just from the
5 paper, make a couple of points because I think we've
6 heard some reasons for caution in thinking that there's
7 claims here from the plaintiff's side. And there's also
8 some reasons to think existing law has some teeth that
9 haven't been brought out.

10 And so the first one, I think, is -- and in
11 interviewing people who do fair lending compliance, there
12 are huge fair lending compliance programs. The level of
13 effort in the major financial institutions in this area
14 is very large. And at least part of the reason is
15 related to a CFPB case in June this year, where GE
16 Capital was ordered to provide, or did a consent decree
17 to provide, \$169 million in remedies for fair lending
18 violations in advertising. And that's just a big number
19 compared to what we're used to in consent decrees and
20 such.

21 And the facts were about advertising to
22 existing customers. As Leonard pointed out, it's
23 especially clear the law applies to existing customers,
24 but according to the facts in the complaint, GE Capital
25 had offered a nice credit deal, you can reduce your back

1 amount that you owe, but it did not extend those offers
2 to any customer who indicated they preferred to
3 communicate in Spanish or at a mailing address in Puerto
4 Rico.

5 And so the violation was that you only
6 advertised in English, you did not advertise in Spanish,
7 you were excluding Spanish-speaking consumers from this
8 very attractive offer and as a result, you know, \$169
9 million consent decree.

10 And I think when you talk to fair lending
11 people, they're aware of ways the law may or may not
12 apply, but they're aware of that level of enforcement and
13 it gives them a different level of seriousness.

14 And so from seeing cases like that over the
15 last 20 years -- that was an unusual one, but cases that
16 have been brought in, I have three very quick points.
17 The first is the FTC has unusual enforcement power under
18 the Equal Credit opportunity Act, so the statute
19 specifically says the FTC can enforce compliance with it,
20 irrespective of whether that person is engaged in
21 commerce or meets any other jurisdictional test under the
22 FTC Act.

23 So, for those of you who have been afficiandos
24 of the FTC enforcement jurisdiction, this is a sort of
25 spectacularly interesting moment in the law that I think

1 is worth noticing. It doesn't have to be somebody
2 engaged in commerce and so there are some important FTC
3 powers here that are not familiar from other statutes.

4 The next one is -- as we wrote this paper and
5 tried to think about fair lending and its history, which
6 is something I worked in a while back, and how it makes
7 sense to privacy people, many of whom are in the
8 audience.

9 The first point is that there is sectoral
10 legislation in anti-discrimination law. And that's
11 really familiar to the HIPAA, Gramm-Leach-Bliley, COPPA
12 sectoral regulation in privacy. And so we have the ECOA,
13 the Fair Housing Act and you have Title VII, so there's
14 existing substantial legal laws in place around lending
15 and housing and employment.

16 And so, for those areas, it's sort of like
17 HIPAA and Gramm-Leach-Bliley, it's time to go do the
18 research and see what those laws cover or don't.

19 And then the last point I'd make is -- similar
20 again for privacy people, those are the HIPAA, Gramm-
21 Leach-Bliley, COPPA regulated parts. And then what do
22 those principles teach us about everyone else? And I
23 think in privacy those laws have been looked at as the
24 structures that people use for a lot of their privacy
25 policies in other areas. They may or may not have all

1 the strictness, but it's the same structures.

2 And so I think the last 20 or 40 years of
3 discrimination law, including fair lending, provides a
4 lot of useful insights about advertising and other
5 practices related to big data. And instead of these
6 issues being brand new -- and this is something that
7 Leonard said -- they've been going back to the '80s and
8 '90s, we have decades of work that's been done here. And
9 I think along with figuring out what we think we ought to
10 do, there's a legal research task about what the law has
11 done. And talking among others, fair lending and
12 employment and fair housing experts to see what's really
13 done there is something that I think really would inform
14 our debate a lot about what the legal rules are.

15 MS. WORTHMAN: Now, going just a little bit
16 into the -- not to beat the Maserati example, but let's
17 say that the list is based on aggregate data that has
18 been prepared by the credit bureaus, on a
19 household level, not on an individual level. What are
20 the implications in the FCRA context for a marketing list
21 that has been prepared using previous purchasing history
22 by consumers just by households? Does the FCRA apply in
23 that context?

24 MS. MILLER: Well, I will -- I think I'll punt
25 on this one, because I think marketing is not necessarily

1 my expertise. It's more FCRA and consumer reporting with
2 respect to other permissible purposes.

3 MS. WORTHMAN: Anyone else would like to take
4 it?

5 MR. PEELER: So just as a general principle --
6 and I actually had the opportunity to work on
7 implementation of the Fair Credit Reporting Act and to
8 work on Reg B when it was issued. And I think just
9 looking back at the structure that's there, if you were
10 using information collected from a third party to make
11 decisions about whether an individual can purchase or
12 obtain particular good or services, I think you do need
13 some structure to provide FCRA type noticing correction,
14 as opposed to if the issue is are you sending an ad out.
15 And I think, you know, one of the things I think is true,
16 Leonard, still is that pre-screening, where you have
17 exercised jurisdiction, still involves making a firm
18 offer of credit, right?

19 MR. CHANIN: That's correct.

20 MR. PEELER: So, again, just looking at the
21 model that's been used for years and years in that
22 industry, if you're making a decision about, you know,
23 what's going to exclude somebody based on third-party
24 information, there ought to be some way to make sure that
25 information is right.

1 If what you're doing is just trying to make
2 information available to consumers, I think that the cost
3 of doing a fair lending type analysis for, you know, a
4 wide variety of products gets to be, you know, very high
5 and very unworkable. And the exception to that, I think,
6 are two of the areas that are represented up here,
7 housing -- you know, that's a limited commodity. If you
8 miss the opportunity to apply for housing, you know,
9 you're not going to get the housing. Jobs is a limited
10 commodity, if you miss the opportunity to get your
11 application in for that job, you're out of luck, you
12 can't come back and get, you know, the extra one of
13 those.

14 MR. EAGAN-VAN METER: So based on the research
15 that LaTanya presented today, would marketing high
16 interest rate/low credit limit credit products on certain
17 websites, based on the consumers who frequent those
18 sites, implicate any of the statutes we discussed today
19 or any others?

20 MR. CHANIN: So I'll take a first jab at that.
21 If you're not talking about housing, but you're talking
22 about other credit, then I think generally speaking the
23 answer is no. First of all, at least my assumption is
24 that someone, anyone, can apply for credit. That is,
25 that if I market it, it's not the sole way or the only

1 way to get credit, because that would raise other issues
2 fundamentally, whether you're discriminating if someone
3 can't call you, go on your website, however you can
4 apply.

5 But assuming that you market and people can
6 contact you independently of that marketing activity,
7 then I don't think that marketing and target marketing
8 would be -- would raise fair lending issues, at least
9 under the Equal Credit Opportunity Act.

10 I think -- you know, as was alluded to by Lee
11 and others, you know, this is not a new issue. That is,
12 people for years have been targeting marketing in radio,
13 television, newspaper subscriptions and so forth, in
14 order to get people who might be interested in their
15 products, whether credit products or other products to
16 respond to those. What we've got now is obviously far
17 more data that people are able to use and manipulate it
18 in order to better target, if you will, to audiences that
19 they think may be interested in their products.

20 The other thing I'll mention is that, you know,
21 it's been -- I wasn't able to attend this morning, but
22 there's a lot of discussion about disparate impact. If
23 you decide to apply the Equal Credit Opportunity Act to
24 credit, you need to talk about disparate treatment. What
25 the law would prohibit is if I have, for example, as was

1 mentioned earlier, a retail shoe store predominantly or
2 exclusively for women, in terms of women's shoes, and I
3 offer a credit product, it would be illegal for me to
4 target -- that is, to send solicitations to advertise
5 solely to women, regardless of disparate impact. That
6 is, de facto discrimination against men would be illegal
7 if you apply the Equal Credit Opportunity Act to
8 marketing, unless you have some kind of carve-outs or
9 something.

10 MR. PEELER: And the two quick clarifications
11 on that is if a man comes in and applies for that credit
12 card, he's got to be evaluated on the same criteria as
13 everybody else does.

14 And your credit portfolio in the credit card
15 area is going to be evaluated against whether there's
16 disparate impact. So the end results are important and,
17 you know, if you're a creditor I'm assuming that you're
18 making sure that your marketing is going to get you to
19 the place where you can survive an examination by
20 Leonard.

21 MR. CHANIN: Not anymore.

22 MR. SWIRE: So, Leonard has lived these issues
23 at the CFPB in recent years and I'm in the midst of
24 getting up to speed again on some of this, so I -- but I
25 would like to point out two things about marketing in the

1 lending area.

2 One is that in the fair lending area there is a
3 history of strongly encouraging targeted marketing to
4 minority communities. So if you go and look at the
5 remedies, the answer is you haven't been advertising on
6 African American radio stations or you haven't been
7 advertising to Hispanic radio stations and you need to do
8 that. So instead of marketing being this sort of bad
9 thing, as you sometimes hear in the privacy debates, it's
10 been a required part of the remedy for fair lending.

11 But along with that, there's a sort of split,
12 which the paper would call the paradox of advertising on
13 lending. And which is that there's a prohibition on
14 what's called steering when you lend and this has been in
15 the rules for a long time.

16 And at least in recent years, after the CFPB
17 sort of saw the subprime crisis and whatever, targeted
18 subprime loans and targeted other loans, I think, has
19 raised CFPB concerns so here's a quote from its guidance,
20 "A creditor may not advertise its credit services and
21 practices in ways that would tend to encourage some types
22 of borrowers and discourage others on a prohibited
23 basis." This is the CFPB language. "In addition, a
24 creditor may not use pre-screening tactics likely to
25 discourage potential applicants on a prohibited basis."

1 So there's at least language that's sort of
2 more -- if you want to call it plaintiff friendly or
3 enforcement friendly, than some sort of categorical idea
4 that this is exempt from the ECOA. And it may be the
5 CFPB is pushing past some of the previous ways that
6 people thought about it at the Fed in earlier years. But
7 there's language that's more pro plaintiff than some of
8 the categorical exclusions would suggest.

9 MR. EAGAN-VAN METER: So to push that a little
10 bit further, if you had a high end credit card and a more
11 sub-prime card, and the sub-prime card was only marketed
12 on sites frequented by minority groups, and the prime
13 card was on, you know, sites that were frequented by high
14 income or, you know, other nonprotected classes, does
15 that count as steering in that way? If you're not, you
16 know, kind of turning someone off, but you're giving them
17 a different offer that might not be as appealing?

18 MR. SWIRE: Is that --

19 MR. CHANIN: You raised the steering issue.

20 MR. SWIRE: I did. And in the pre-call with
21 Leonard, I said, Leonard, even at the CFPB when is it
22 good to do a targeted marketing to make up for past
23 problems and when is it bad to steer and can you point me
24 to the authoritative source on that? And we weren't able
25 to identify an authoritative source.

1 So I think this is a real puzzle. And my paper
2 suggests it needs a lot more discussion than we've had
3 today. But maybe, Leonard, you have more?

4 MR. CHANIN: Yeah. I guess what I would say is
5 the fact of marketing those products to different either
6 audiences or different websites, in my view, does not
7 violate the Equal Credit Opportunity Act.

8 However, as I think Lee alluded to earlier, if
9 your portfolio -- if you have data and, you know,
10 sometimes lenders do not have this data, but if you have
11 data that shows ethnicity or gender or age, and so forth,
12 in those portfolios then certainly there are going to be
13 questions about why do you have such a skew in terms of
14 who has these credit products. Do you make them
15 available to everyone? If someone calls up, goes on your
16 website and applies, do you steer them? That's going to
17 raise very different issues.

18 But the fact that people respond to certain ads
19 and other people respond to different ads, I don't think
20 raises that type of issue. It's simply, what does the
21 portfolio look like at the end of the day and how will
22 you explain those, if there are dramatic differences.

23 MR. SWIRE: Can I follow-up just on -- so, it
24 was interesting what Leonard said, if you have the data
25 in your portfolio that indicates a skew, that's

1 reminiscent of having HMDA data, Home Mortgage Disclosure
2 Act data, that shows a potential skew and then regulators
3 historically have looked more carefully at it.

4 The paper I wrote suggests that that data about
5 likely demographics may well be available in online
6 marketing in a lot of ways it wasn't historically for
7 lending. So a lot of online marketers are pretty sure
8 they have a pretty good fix on their market and so there
9 may be data inside their big data sets that say with some
10 level of confidence what are the demographic, you know,
11 characteristics.

12 And if you have that and you have a disparate
13 impact in the data in your database, the history under
14 fair lending has been that you might come under scrutiny,
15 at least for the regulated industries, I think.

16 MR. PEELER: Well, and I think one other risk
17 would be -- if in the hypothetical you raised, if somehow
18 when -- if the consumer goes back to that creditor, not
19 in response to the ad, but goes back to the creditor site
20 and somehow the products that that consumer is able to
21 access on the website is limited to products that fit a
22 particular profile, then I think you probably do start to
23 engage -- have some serious issues.

24 MR. SWIRE: Let's call those landing pages that
25 might be different for customers of different sorts.

1 MS. WORTHMAN: Going to -- actually, following
2 up a little bit on some of the panel discussions from 1
3 and 2, they discussed aggregate credit scores. How is
4 the industry applying the FCRA analysis to these scores?

5 MS. MILLER: So I'll say -- I'll start that
6 one. With respect to employment and the FCRA and the use
7 of that data for employment screening purposes, there is
8 a common misperception that these credit scores are used
9 for screening purposes and they're not.

10 And so, therefore, if you were to request a
11 report on an individual and you're a consumer reporting
12 agency and you're providing that to an employer, it's not
13 going to include a credit score. It may include credit
14 information, but it's not going to include a score.

15 So, taking that off the table, although I know
16 that there's a lot of -- the media certainly reports at
17 times that scores are used for employment screening
18 purposes, in fact, they're not used for that purpose.

19 Now, I think that if you have just the general
20 aggregate scoring and you're looking at certain
21 communities, I think then it would turn more to a
22 discussion about the discriminatory impact of the use of
23 that type of data.

24 MS. WORTHMAN: So how is that implicated,
25 Carol, with the fact that when somebody applies for a job

1 they can definitely give their consent to have the
2 employer look at their credit history. But even if
3 they're following the FCRA, how does it impact with Title
4 VII?

5 MS. MIASKOFF: Right. Well, even if someone
6 gives their consent to doing, you know, getting the
7 credit background, if the employer uses it as a reason
8 for excluding someone from employment and if using that
9 has a disparate impact, and is not -- and the key is, is
10 not job-related and consistent with business necessity or
11 even if it is, there could be a less discriminatory
12 alternative. In that case, it's going to be
13 discriminatory, regardless of the consent. So that's the
14 bottom line there.

15 MS. MILLER: And I just wanted to piggyback off
16 of that. I mean, certainly, consent is the first step in
17 terms of pulling such a report for employment screening
18 purposes. I will say also that credit is not as
19 frequently used as one would believe that it is. There
20 are other -- there's other data in the reports that is
21 more frequently used. And credit tends to be very
22 specific to a position, which would blend nicely with
23 Title VII and what Carol was talking about.

24 But that's the baseline, is you have to have
25 the individual's consent.

1 MS. MIASKOFF: I would just add that as a very
2 practical matter there are probably not many employers
3 out there, looking at the whole landscape, who understand
4 how to read the kind of information they get when they
5 get one of these financial reports about someone.

6 And I think probably that's why everyone talks
7 about credit scores, because that's something that a lot
8 of us can understand. But when they get a lot of other
9 information it's often hard for them to put it in context
10 and, you know, therefore, an employer might just say, oh,
11 we got a hit, you know, we have something. And then
12 potentially exclude someone.

13 MS. MILLER: Which I would say is why credit,
14 with respect to employment screening, is used sparingly
15 and scores are not used. In fact, there are contractual
16 restrictions to the use of scores if your permissible
17 purpose is for employment screening when working with one
18 of the bureaus. And certainly with the reports
19 themselves, it is important to understand what they say.
20 And there are also, even at the state level, quite a few
21 restrictions on the use of credit if it is, in fact, for
22 employment screening purposes.

23 So I think credit is an area that is highly
24 regulated, whether it's FCRA or state statutes.

25 MS. WORTHMAN: And then taking a question from

1 the audience, Carol, you said earlier that big data, if
2 it has a disparate impact but it's predictive of job-
3 related outcomes, that it's not illegal. Does that mean
4 that the better the data set the more likely it is to
5 comply with the law?

6 MS. MIASKOFF: I guess the more likely, yes.
7 But whether or not it, in fact, complies is the actual
8 question. And the issue is going to be, just to sort of
9 clarify, really whether or not the criteria used to
10 screen someone out for a particular job, you know, is
11 relevant for performing that particular job.

12 And I guess I didn't mentioned before, but one
13 of the ways in which you could say the EEO laws
14 anticipated big data, is that we have at this point,
15 quite -- from 1978 some guidelines in place about
16 validating selection tools for employment. And they were
17 written initially about tests. And the question was if a
18 test had a disparate impact, how do you know if it's job-
19 related for the position in question and the tasks in
20 question.

21 And it has three ways of validating. And I
22 think it's really going to be interesting to see how
23 those principles can be applied in the big data context.
24 But it is for the job in question.

25 MR. SWIRE: Can I follow-up on that?

1 MS. WORTHMAN: Yes.

2 MR. SWIRE: So there's a Sears case with
3 employment about -- it turned out men were more likely to
4 do certain high commission sales and women were more
5 likely to be near the front of the store selling smaller
6 items.

7 And Sears was able to come up with a
8 statistical study in the case that showed a business
9 necessity that it was actually based on the choices of
10 the individuals who had picked these different jobs. In
11 that case Sears won, the defendant won, but it won after
12 having a pretty substantial burden of proof to show the
13 validation on the statistics.

14 MS. MIASKOFF: Yeah, it's not easy.

15 MR. SWIRE: And so I think in the marketing
16 area, the fair marketing or whatever we call it, one of
17 the changes, if this law turns out to apply in these
18 sectors, may be that the practices meet business
19 necessity, but there would be a compliance effort by the
20 companies to show the validation. And I think up until
21 now that effort to do that validation has not been the
22 industry standard in a lot of places. And to meet the
23 laws, it might become or have to become the industry
24 standard.

25 I'm curious from the employment side, does that

1 match your understanding of the law, at least in the
2 employment side?

3 MS. MIASKOFF: Well, as a -- I wouldn't say
4 it's more whether it matches my understanding of the way
5 businesses are complying with the law or not.

6 MR. SWIRE: Right.

7 MS. MIASKOFF: The reality out there is I think
8 Federal contractors, because of all of the requirements
9 that come with a Federal contract, do a lot more
10 validation now than companies that are not contractors.

11 I know from EEOC's perspective, we regulate all
12 private sector employers with 15 or more employees and
13 one thing we really are pushing now is the kind of
14 record-keeping that can facilitate validation.

15 MR. SWIRE: But there may be a due diligence
16 effort here expected from the companies that has not
17 maybe been built in, up until now.

18 MS. MIASKOFF: And I think that could be a very
19 positive thing, actually.

20 MS. WORTHMAN: Now, going to another example of
21 the use of, or the potential use of, big data. So, in
22 2008 the FTC brought a case against a credit card
23 marketing company that was looking at the shopping habits
24 of its consumers and actually based on where the
25 consumers were shopping decided to lower the credit

1 limits of certain consumers and actually then charged
2 over-limit fees as a result of that.

3 But now, since there is this proliferation of
4 information where you can purchase data of where people
5 shop or use that, what are the implications, for example,
6 if a creditor would offer credit terms, better credit
7 terms, to people who shop at Walmart versus 7-Eleven.
8 Or, if in the employment context, if an employer was
9 relying on these sort of marketing lists to determine who
10 they would advertise jobs to or who they would hire?

11 MS. MIASKOFF: Well, I'll just jump in starting
12 with employment. The question would be whether -- you
13 know, we'll look at the data and is that causing a
14 disparate impact on one of the basis protected by the
15 Civil Rights Act or one of the other laws. And if it
16 did, then if it were not job related consistent with
17 business necessity, it would be discriminatory.

18 MS. MILLER: And from the FCRA perspective,
19 what I would look to in that type of a situation is just
20 who is preparing the reports and what's being included in
21 those reports. Because, you know, from the employment
22 context you have to have a consumer reporting agency who
23 is assembling and evaluating the information, providing
24 it to a third party, and then it's for one of the seven
25 factors and it's being used for permissible purpose.

1 So the question would be, do you meet all of
2 those, do you fall within or outside of the FCRA? But
3 certainly those are questions that come up regularly when
4 companies try to promote new products and whether it will
5 be, in fact, an FCRA product or not. So you'd have to
6 look at those factors.

7 MR. PEELER: It sounds like your hypothetical,
8 there actually is a decision being made about the
9 customer, in terms of what the rate is for their credit
10 card, so that's clearly covered by existing law.

11 The one sort of additional nuance that I would
12 throw into the mix, though, is, you know, again talking
13 about the need to segment the conversation about big
14 data, if the information is collected online to support
15 online behavioral advertising, the advertising industry
16 self-regulatory guidelines say you can't use that for
17 employment insurance or credit decisions, period. You
18 can use it for marketing, you cannot use it for
19 decisions.

20 MR. EAGAN-VAN METER: So to follow-up on that,
21 how frequent are contractual disclaimers? Such as the
22 prohibitions that you're referring to, kind of banning
23 the use of that type of data for FCRA purposes.

24 MS. MILLER: Well, it didn't work out too well
25 for Instant Checkmate. But, I mean, certainly it's

1 something that -- you can't have a disclaimer, I would
2 argue, and expect that the FTC wouldn't look at it very
3 carefully. And especially if your disclaimer happens to
4 be -- even though we have -- and I'll just use big data,
5 because that's what we were talking about -- even though
6 we happen to have big data and even though we happen to
7 be selling it to you and even though you happen to be
8 looking at it, and maybe, perhaps, kind of/sort of you're
9 looking at it for employment purposes or housing, we're
10 not a consumer reporting agency, this is not an FCRA
11 product.

12 The FCRA, I think, can be -- in fact, is very
13 effective. And I think FTC is very effective at
14 enforcing the FCRA. So, disclaimers are certainly
15 something that don't bode well for the company who --
16 especially if you're trying to say that you're not an
17 FCRA product when, in fact, you meet all the elements of
18 it, whether it's employment or tenant screening or if
19 you're using, as I said, the data and you fall under the
20 elements of what is a consumer reporting agency.

21 But on the other hand, you know, that is one
22 that some would argue that the FCRA covers consumer
23 reporting agencies, but it leaves a bit of a hole when it
24 comes to employers who may be using that information
25 themselves and not operating or using the services of a

1 consumer reporting agency. So, in that situation we'd
2 have a different analysis.

3 I wowed everybody into silence.

4 (Laughter.)

5 MS. WORTHMAN: What about the use, though,
6 again going back to some of the more sort of aggregate
7 data, nontraditional credit information, that's being
8 used, whether it's Government records, social media,
9 shopping habits, web tracking, location data?

10 If that is being used in the marketing context,
11 both in the credit and non-credit space, is that
12 something that is -- is there a gap there with the
13 statutes and the regulations?

14 MR. CHANIN: I'll take a try at it. I guess
15 the question is -- where do I start with it. So if you
16 think about amending the various laws, the question to me
17 first would be is there injury, is there harm to
18 consumers? Because you need to balance that against
19 counter-veiling benefits.

20 You know, if someone is sending marketing
21 materials based on whatever information, targeting to
22 individuals, presumably there is some benefit to those
23 individuals who receive it. Requiring that information
24 to be sent to every individual, many of whom have no
25 interest in it, is probably not going to be very

1 beneficial, it also is going to increase ultimately
2 the price of the product, lead to other techniques
3 to market and so forth.

4 So, to me, the question is, is there injury.
5 It seems to me there would be injury if, for example, I
6 market through one channel or multiple channels. If the
7 terms, as Lee, I think, alluded to -- if the terms of
8 that credit are only available through that channel and
9 someone contacting me through a website, through a
10 telephone, in-person mail, cannot get those terms, they
11 get terms that are less desirable, then that certainly
12 could raise questions of injury.

13 If that's not the case, then the question to me
14 is fundamentally are there consumers being harmed by not
15 receiving a particular offer.

16 MR. PEELER: And if you expand it beyond
17 credit, you know, you get pretty quickly to, you know,
18 examples where it doesn't make any sense, you know, which
19 would be the -- you know, cosmetics and shavers and, you
20 know, music. And you also probably get very quickly to
21 some areas where it would be unconstitutional, like,
22 birth control or marketing political material.

23 MS. MILLER: And I think there's a very
24 interesting and fascinating intersection with the use of
25 social media. We've talked about that a lot today with -

1 - between the FCRA and consumer reporting agencies who
2 are providing social media information for, say,
3 employment purposes and then just EEO laws. Because
4 certainly under -- employers are using social media,
5 whether it's private employers, whether it's Government,
6 social media is used.

7 And so there's sort of this split between well,
8 what happens when an employer looks at it and Googles a
9 candidate and then what happens when a consumer reporting
10 agency prepares a report that includes social media
11 information. And if it's a consumer reporting agency,
12 it's going to be very restricted, if you will, and very
13 calculated and carefully synchronized with what the Fair
14 Credit Reporting Act would say with respect to reporting
15 that information. But they're only going to be looking
16 at certain things, it's a much smaller universe, whether
17 its illegal activity or racist comments or explicit
18 photos.

19 I mean, that's what a consumer reporting agency
20 that would look at and provide a report that includes
21 social media would look at, because what they want to
22 factor out for their sake and for employers' sake are the
23 discriminatory elements that one could see if, for
24 instance whether it's religion or maybe -- certainly
25 gender, that you would see if you were just an employer

1 who is Googling it.

2 So, certainly, I think that's an area where
3 FCRA provides a lot of protections for consumers, if an
4 employer is, in fact, going to request a report that
5 includes social media.

6 MR. SWIRE: Here's one distinction that hasn't
7 been brought up in the panel. Under ECOA, you don't
8 usually think of there being different loans to women or
9 men. And, in fact, one big reason why the Equal Credit
10 Opportunity Act exists was to correct for a history where
11 married women didn't get their own credit history, it was
12 just the husband's credit history. And divorced women
13 turned out not to have a credit history and couldn't get
14 a loan, once they were divorced.

15 So, in the credit area we don't expect there to
16 be men's loans and women's loans, or black loans and
17 white loans. That would be very -- we'd be extremely
18 skeptical of that in a credit relationship. The shavers
19 and cosmetics categories, although shavers, I believe,
20 are used by both sexes, but --

21 MR. PEELER: Not the same ones.

22 MR. SWIRE: Well, I don't know the facts on
23 that.

24 (Laughter.)

25 MR. SWIRE: Anyway, in cosmetics you can get

1 into your own discussion. But I think for some universe
2 where there does seem credit related and we have some --
3 there's some uncertainty about what sort of things are
4 going to be credit related, it might turn out there's
5 advertising that's directed more towards one sex or
6 another, one national origin group or whatever.

7 And where one of these statutes applies, it
8 doesn't mean that you can't, under the law, turn out to
9 have a women-targeted ad or a men-targeted ad. If one
10 of the discrimination statutes applies -- lending,
11 housing, employment -- my understanding is then it's a
12 business necessity defense. You get to do it because
13 we have to do that in order to sell the cosmetics or
14 whatever it is.

15 But there's a prior question of when are these
16 statutes going to apply and once they do, you can have a
17 defense of necessity, but then the company has to come
18 forward and show the facts supporting that.

19 MS. WORTHMAN: Building a little bit more on
20 the social media comment, what about employers who look
21 at social media to determine hiring eligibilities? Or
22 also in some lending context where people look at how
23 many friends you have or who your friends are in
24 determining whether or not you're eligible for credit.

25 MS. MIASKOFF: Right. Well, in just looking at

1 employment, employers who look at social media as part of
2 the screening of applicants, you know, frankly, it puts
3 them, I would think, in a vulnerable position, vis-a-vis
4 the EEO laws. Because, obviously, with many social media
5 you take one glance at it and you learn, you know, a
6 plethora of information about various protected statuses
7 the person may have.

8 And once the employer has that information, if
9 they deny the job to the individual or they deny the
10 promotion or the training, and the person is trying to
11 think, gee, why didn't I get this? And they happen to
12 find out, perhaps, that social media was looked at. You
13 know, it's -- they may well bring a charge to challenge
14 it.

15 And so from an employer's perspective you
16 really have to step back and think am I going to get
17 something that's really, you know, related to job
18 performance and worth my while here for taking that risk.

19 MS. MILLER: And I would also say with
20 employment, in bringing it back to the FCRA, the biggest
21 challenge with social media is just accuracy.

22 MS. MIASKOFF: Yes.

23 MS. MILLER: And -- so which is why consumer
24 reporting agencies would just look at user generated
25 content, as opposed to any content that's out there. And

1 then the other question, of course, which is not so much
2 FCRA, just as its terms of service or their privacy
3 policy, is depending on how you capture that social
4 media. A consumer reporting agency would need to look at
5 just what's publicly available. You have to be careful
6 not to go beyond the bounds of a company like a Google or
7 a LinkedIn or Instagram's either privacy policy or terms
8 of service and capture information that is in violation
9 of either of those.

10 MR. SWIRE: A question on whether there could be
11 another concern about social media being used in
12 recruitment, for instance for employment, it may well be
13 that people have a lot of friends who come from the same
14 ethnic, racial, whatever background as themselves --

15 MS. MIASKOFF: Right, right.

16 MR. SWIRE: -- and so if you're trying to have
17 diverse recruitment and it turns out you're sort of going
18 down a path that's very dependent on one group, that
19 could raise the EEO question as well.

20 MS. MIASKOFF: It does raise EEO questions.
21 And the answer to it is that you have to recruit through
22 many different sources and avenues and tools to sort of
23 counter-balance that. I mean, there's also just an issue
24 in terms of, you know, computer access, period. Smart
25 phone access, which many more people have now, but still

1 there are people who don't have it. And you certainly
2 can't access as well some things on a smart phone as on a
3 computer.

4 I'd also add with the social media, as you may
5 be aware, there are many states now that have laws that
6 prohibit employers from requiring people to give them
7 their social media passwords to check it out. There was
8 pending Federal legislation, but that has not gone
9 anywhere. Though I've certainly heard stories that
10 despite that legislation you have employers saying, now
11 I'm going to turn my back so I don't get the password,
12 but log in now and I want to see it.

13 MS. WORTHMAN: And in the credit context,
14 Leonard, with the social media?

15 MR. CHANIN: So, I think you've got to divide
16 between the marketing, based on that information, versus
17 a customer. So there is nothing in Regulation B that
18 prohibits use of the information, but I would be very
19 careful because as was suggested before what's on that
20 website, if you have gender, racial information,
21 ethnicity, age and so forth. If you look at that and
22 then there's going to be certainly an allegation or
23 potential allegation that you've considered it, either --
24 certainly if you have an existing customer, in terms of
25 that customer relationship, potentially with marketing if

1 you have that, certainly there will be questions to
2 follow.

3 So I'd be very careful about using it. Even
4 though there's nothing that directly prohibits use of
5 social media, at least in the context of credit
6 transactions.

7 MS. MIASKOFF: And I would just add, with
8 social media and employment -- although I think probably
9 the rule, rather than the exception, is people tend to
10 have as their friends, they have people from similar
11 backgrounds as themselves. I know, you know, sometimes I
12 have a variety -- I'm just using myself as an example --
13 a variety of friends and as a result of that I get some
14 very interesting suggestions from Facebook as to, you
15 know, what group I might want to join or whatever, what
16 publication I might want to follow. And were an employer
17 to look at that, they could, you know, then draw
18 conclusions about me.

19 So there's really a lot of vulnerability for
20 employers.

21 MR. EAGAN-VAN METER: Are current categories or
22 protected groups under anti-discrimination and consumer
23 protection laws sufficient? Panels 1 and 2 discussed
24 victims of crime or domestic violence, as well as people
25 with particular health statuses.

1 MS. MIASKOFF: I would jump in. I mean, I
2 think basically, yes. In terms of health status, with
3 the expanded definition of disability that came into
4 effect in 2009, there are a lot of health statuses that
5 are covered by the ADA now.

6 I think, you know, societally we may -- you
7 know, the big categories that are covered are the ones
8 that our society has had major, major problems with. And
9 I think that's sort of an appropriate focus for these
10 laws. In terms of abused women, I think possibly the
11 gender -- gender could capture that, possibility
12 disability in some ways.

13 MR. EAGAN-VAN METER: How effective are adverse
14 action notices under ECOA at conveying an adverse credit
15 decision, where that decision might be based on thousands
16 of big data variables?

17 MR. CHANIN: I don't know who is taking that one.

18 MR. EAGAN-VAN METER: You have an
19 audience member to thank for that.

20 MR. CHANIN: I'll stall and let them have time
21 to think, but only because Katie has told me that we are
22 going to discuss big data and NSA before we leave today.

23 MS. WORTHMAN: No comment.

24 MR. CHANIN: How can you have a discussion
25 about big data without discussing the NSA?

1 I think the answer to that question is, at
2 least to my knowledge, we don't know. Adverse action
3 notices, you either have to give automatically the reason
4 for the denial, they have to be specific, or the consumer
5 has the right to get the specific reasons. They have to
6 be pretty detailed, so if you use credit report
7 information or any other information, you have to give
8 enough information so that a typical consumer can
9 understand exactly what it is.

10 So if the person has been late in making
11 payments, if he or she has a charged off account, filed
12 for bankruptcy, all of those sort of things have to be
13 clearly communicated. What's not clear is -- or at least
14 I'm not aware of any data that has studied, you know,
15 what consumers do with that information. To the extent
16 they can, are they able to correct the information moving
17 forward, or how do they use that information.

18 It might be an interesting research topic, but
19 I'm not aware of any data on that.

20 MS. MILLER: And I would just say under FCRA, I
21 mean, certainly adverse action notices are built into the
22 FCRA. It's an important part of it, whenever you're
23 using a consumer report and it's for one of the purposes,
24 whether it be employment or tenancy or credit, you have
25 to provide the adverse action if any information from the

1 report, including maybe if it's credit information, is
2 used in whole or in part to make an adverse decision.

3 And then take it one step further, you have
4 employment and there is an additional pre-adverse action
5 step that needs to be followed. If information in a
6 report is going to be used adversely against an
7 individual, they must be provided notice of that and a
8 copy of the report and a summary of their rights. So
9 certainly adverse action is built into FCRA.

10 MR. SWIRE: One other thing about adverse
11 action notices is it's not just whether that individual
12 cures their problem. Another role of them is an
13 enforcement regime overall, so if there's an adverse
14 action notice that might end up with an advocacy group or
15 a plaintiff's lawyer realizing there's some practice that
16 should be challenged and maybe a complaint to a
17 regulator.

18 And if they're not being issued the adverse
19 action notices, that can get detected with the company
20 and lead to enforcement.

21 So it's part of an overall structure to detect
22 things that might turn out to be troublesome and it's not
23 just the individual fixing their own credit.

24 MR. PEELER: And so, as historian of the panel,
25 to put a little context on that discussion. You know,

1 the adverse action, ECOA, Fair Credit Reporting Act
2 structure, you know, created a dynamic where you have
3 greatly expanded, where big data greatly expanded credit
4 availability to consumers, made the decision making a
5 whole lot more objective and built in some checks and
6 balances.

7 So, you know, like one of the big challenges
8 that was alluded to this morning for big data in the
9 credit area is to expand that model to, you know,
10 consumers that currently can't be credit-scored.

11 MS. WORTHMAN: Lee, you have the last word on
12 that.

13 I'd like to thank all of our panelists for the
14 discussion, it's been very informative.

15 (Applause.)

16 MS. WORTHMAN: And we are now going to take a
17 break and return at 3:15. Thank you.

18 (Whereupon, there was a brief recess.)

19 PANEL 4: CONSIDERATIONS ON THE PATH FORWARD

20 MR. OLSEN: Thanks, everyone, for joining us for
21 the final panel. We're here talking about big data. A
22 lot of people talk about leaving digital footprints.
23 Somebody left physical evidence of their person in the
24 lady's room, some reading glasses. They're up here to be
25 claimed.

1 I know there's no coffee allowed in here, which
2 I think is sort of a disaster for the last panel of the
3 day. So, we screwed everything up, didn't we? We have
4 screwed everything up, and we haven't even started.

5 MR. CALABRESE: I blame the FTC.

6 MR. OLSEN: All right, this panel is on paths
7 forward. I have a very distinguished group of panelists
8 here with me. It's going to be a challenge for all of us
9 because a number of panelists earlier in the day
10 discussed steps forward. So, this panel is challenged to
11 come up with something new and different for the last
12 panel, but I'm sure they're up to the task.

13 Just quick introductions. I should have
14 borrowed the reading glasses that I just had. To my left
15 is Chris Calabrese who is the legislative counsel for
16 privacy related issues in the ACLU's Washington office,
17 where his portfolio includes internet privacy and new
18 surveillance technologies.

19 Next to him is Dan Castro, a senior analyst at
20 the Information Technology and Innovation Foundation and
21 the director of the Center for Data Innovation.

22 Jeanette Fitzgerald, next to Dan, is general
23 counsel and chief privacy officer for Epsilon, where she
24 leads the government affairs legislative and regulatory
25 initiatives related to data protection and privacy.

1 Jeremy Gillula, did I pronounce that right?

2 MR. GILLULA: Yes, you got it.

3 MR. OLSEN: All right. He's a staff
4 technologist at EFF, the Electronic Frontier Foundation,
5 where he focuses on privacy and civil liberties issues
6 arising from new technology.

7 Next to Jeremy is Michael Spadea, a director at
8 Promontory Financial Group, where he advises clients on a
9 wide range of regulatory and compliance issues related to
10 privacy and information governance.

11 And, last, but not least, Chris Wolf is a senior
12 partner at Hogan Lovells, where he leads the firm's
13 global privacy and information management practice. Also
14 the founder and chair of the Future of Privacy Forum and
15 chair of the Anti-Defamation League, National Civil
16 Rights Committee.

17 So, to kick us off, I want to do something a
18 little bit different, and I didn't warn the panelists
19 about this in advance. So, this is a classic moderator
20 foul, but I'm going to proceed anyway.

21 MR. GILLULA: We were told there would be no
22 quizzes.

23 MR. OLSEN: So, I'm going to start with sort of
24 a McLaughlin Group style question. There's been a lot of
25 discussion today about practices that are occurring and

1 could occur. And there's been discussion about the legal
2 landscape and the regulatory landscape.

3 I'd like to ask each panelist for a yes or no
4 answer to the following question. You can say it
5 depends, but that's really cheating. So, I wouldn't go
6 with that. Do you agree that there are currently uses of
7 data, or potential uses, that are harmful that are not
8 addressed by the current legal or regulatory landscape?

9 Chris?

10 MR. CALABRESE: Yes.

11 MR. OLSEN: Dan?

12 MR. CASTRO: I don't think we've heard any
13 today.

14 MS. FITZGERALD: No.

15 MR. GILLULA: Definitely.

16 MR. SPADEA: Gun to my head, no.

17 MR. WOLF: So, I'm a former litigator, and I
18 would never let a witness answer a yes or no question
19 that needs explanation, so we'll be discussing this.

20 MR. OLSEN: Okay, it sounds like we've got a mix
21 on the panel. I think before we get too much into
22 specifics about how we might move forward, it might
23 behoove us to flesh out a little bit of the answers that
24 have been given to the simple question there.

25 I would ask each panelist to talk about whether

1 there are legal gaps or market failures that are not
2 being addressed in the first instance. I'll just start
3 with Chris.

4 MR. CALABRESE: Sure. So, just to give a frame
5 for this, data is not bad. It's not good either. It
6 just is. It's a fact of the environment, so it reflects
7 existing disparities in our society. You know, we see a
8 lot of money in this country that is distributed along
9 racial lines. So, we are going to see those
10 distinctions.

11 I believe the wealth gap in this country --
12 white households now have approximately 20 times the
13 average household wealth of black households. So, the
14 data is going to reflect that. So, our job here is to
15 make sure that big data does not exacerbate it and then,
16 ideally, hopefully down the road, can help to close it.
17 But let's start by not exacerbating it.

18 So, potential regulatory gaps, I am very
19 comfortable saying that there are regulatory gaps, and
20 I'll give you a couple. One of the major ways that big
21 data and data is combined today is in background checks.
22 So, if you want to see whether somebody's got a criminal
23 background or not, and I know it's covered, is you do
24 this background check. Lots of public data sources are
25 checked.

1 We see Chris Calabrese's criminal record in
2 Texas. That is not true, by the way. So, Chris
3 Calabrese probably doesn't get a job. Well, we've seen
4 lots and lots of examples where there are multiple Chris
5 Calabreses, and there are, and those are mixed up.

6 Well, I see a great and classic example for a
7 market failure here because the customer is not Chris
8 Calabrese. The customer is the company, and he or she, it
9 may be willing to deal with a certain level of error if
10 it improves their bottom line which is not to hire
11 somebody with a criminal record. They may be willing to
12 accept a certain amount of data problem in order to deal
13 with that larger problem.

14 Similarly, I have a product that detects fraud,
15 right. If I'm a big bank, I'm really excited if I cut my
16 fraud down by 40 percent. If I have two or three percent
17 of people who aren't able to get a product or have to
18 jump through more hoops to get a product, that's fine,
19 because that's not really what I'm worried about, right.
20 My desire is to reduce fraud. I'm willing to accept a
21 certain amount of error to do that. If some people don't
22 get products, you know, that's too bad, but again, the
23 market isn't going to fix that.

24 So, I'll just leave it at those two.

25 MR. OLSEN: How about you, Dan?

1 MR. CASTRO: So, I think what's really
2 interesting about conversations like we've had today,
3 which has been very productive because we have a chance
4 to have a lot of voices in the room share where they do
5 think there are problems. So, you know, listening to the
6 discussion today, and that was to my answer, you know, I
7 didn't hear a lot of real specifics about where there was
8 something that wasn't being addressed today, where
9 somebody was standing up and saying, look, this is how
10 I'm being harmed today, and this is the reason nobody can
11 take an action.

12 I think that's what we have to talk about when
13 we talk about regulatory gaps. It's not enough to say
14 there might be a problem. The reason this matters is
15 because there is so many opportunities to use big data.
16 That was, you know, part of what the first panel talked
17 about.

18 So, when we're talking about regulatory actions,
19 we know there can be unintended consequences. There's
20 always unintended consequences with any action. So, we
21 have to be asking, you know, can in this case the FTC
22 make a good cost benefit analysis of any type of proposed
23 action, any type of proposed intervention. You have to
24 know what the costs are. You have to know what the
25 savings will be.

1 But just to also pick up on something that Chris
2 had said. You had said, you know, data just is. I guess
3 it depends on what your definition of "is" is here. But
4 I think that's actually the wrong approach. We just came
5 off the legal panel, so, you know, I'll throw it back to
6 Lawrence Lessig and his famous line about code is law.
7 In this case, data is law.

8 Data isn't natural. It's something that's
9 created. We have to think about how it's created and the
10 implications of this creation. Part of us doing that
11 helps solve some of these types of problems that we
12 confront. That's not a regulatory solution; that's a
13 technology solution.

14 MR. OLSEN: Okay, I want to come back to you,
15 Dan, a little bit later and talk to you about how that
16 squares with what you've written about in terms of the
17 data divide and the concerns about collecting data from
18 sources that may not be equally available to all
19 particular groups and whether that presents a problem,
20 maybe not necessarily from a regulatory perspective but
21 maybe from a policy-making perspective. So, hold on to
22 that thought for the future.

23 Jeanette, how about you?

24 MS. FITZGERALD: Sure. But first off, I'm glad
25 you're coming back to him because I wanted to hear more

1 of what he was going to say, too. I wish he had kept
2 going.

3 So, I said no because I think there's a lot of
4 self-regulation that I think already exists. The DMAs
5 out there, the IAB, and there are several other of those
6 As and Bs and all those other groups that have all self-
7 regulatory guidelines.

8 I know for the DMA they will enforce those
9 guidelines among their members. If they hear about
10 somebody who is not a member, they will go talk to them
11 and try and get them to act in what is considered an
12 ethical manner among that group. If they then still find
13 that there's a problem, they've been known to turn those
14 companies over to the FTC so they can look at them
15 further.

16 So, if there's a problem that somebody thinks
17 is in a gap, then maybe we can address it that way
18 without having to come up with another law that will only
19 deal with a certain or a broad-ranging area. But it
20 won't get to what the real problem is, because, as you
21 said, all I've heard in all those reports that came out,
22 they said it's possible there could be a harm. It's
23 possible, but I couldn't find one either.

24 MR. CALABRESE: I have more.

25 MS. FITZGERALD: Okay, good.

1 MR. OLSEN: How about you, Jeremy.

2 MR. GILLULA: So, approaching this from sort of
3 a technologist perspective, I mean, I said yes, because
4 just thinking about it from a statistical perspective.
5 If you're trying to classify something and you get, you
6 know, a 97 percent success rate, that's amazing. That's
7 what people get tenure for if you can pull that off.
8 That means you've still got three percent that are wrong.

9 If you're talking about classifying every person
10 in this country, that means you're wrong six million
11 times, you know, or more, if you've got a two or three
12 percent error rate. That's a lot of people that your
13 automated decision making based on big data could be
14 harming.

15 I think it's a different thing when you're doing
16 a scientific study using big data. You're looking at a
17 lot of data about health and trying to make a
18 determination about, you know, what causes this disease.
19 It's a different thing when you're testing it on people.
20 It's tough to tell when you actually have a false
21 positive or a false negative.

22 So, I think from a technology perspective, we
23 need to make sure that the underlying technology is
24 really working as we think it should.

25 MR. OLSEN: Okay, thank you.

1 Michael.

2 MR. SPADEA: I think it's really too early to
3 tell whether or not there's a gap in the regulatory
4 regime. Even if there is one, we then have to -- I
5 really think you have to go back to the harm discussion
6 and define that. We really haven't agreed on what harm
7 is. How can you have a discussion to determine whether
8 or not there's a gap or, you know, what the remedy is if
9 you don't know what the harm is that you're trying to
10 protect. So, I think that's one of the key places where
11 the conversation needs to start.

12 We heard a lot about risks today. I think you
13 could always prove a point with some anecdotal stories.
14 The goal is not to develop a perfect regulatory regime.
15 If you went out and tried to do all the thinking to put
16 in place a regulation that would prevent every single
17 type of harm, that would pretty much just kill the
18 economy. That's not the goal.

19 How do we allow big data and emerging
20 technologies to deliver the greatest amount of benefit
21 with the least harm to consumers? Obviously, there
22 ought to be a threshold of harm, but there's a lot of
23 benefit. But a lot of harm, that's probably not a very
24 good idea.

25 But even where we think that there needs to be

1 some regulation or some remedy, just as Jeanette pointed
2 out, we should be looking first to what is the least
3 amount of interventions into the economy that is
4 necessary and then sort of gradually increase the level
5 of intervention as necessary. I think we have a little
6 ways to go before we have evidence that there's a
7 regulatory gap.

8 MR. WOLF: So, I think the other Chris really
9 hit it on the head when he says that data is neither, per
10 se, good nor bad. I think that really ought to be the
11 guiding light here, because we have seen that there's
12 enormous potential for good with the use of big data.

13 I think we're going to get into this a little
14 bit later, but thanks to Mark MacCarthy for previewing
15 the study that the Anti-Defamation League and the Future
16 Privacy Forum did on the beneficial uses of big data to
17 identify discrimination and therefore to come up with
18 remedies for it and also big data as a tool to fight
19 discrimination.

20 So, this is the baby and the bath water theory of
21 regulation that I typically espouse. We need to be
22 careful when we're identifying potential problems or even
23 real problems in regulating in a way that throws the baby
24 out with the bath water, and that might have the
25 unintended adverse consequence of inhibiting the positive

1 uses of big data. I know the FTC has that in mind.

2 It's been, I think, a balanced day, and I'm
3 hoping this panel will continue to be a balanced
4 discussion of that issue.

5 MR. OLSEN: Thanks, Chris. I wanted to follow
6 up on two different comments, one that Jeanette made
7 about self reg. I just wanted to pose a question
8 following on Latanya's presentation and ask about the
9 Omega Psi Phi example, the ads being shown related to
10 getting your arrest record, hiring a criminal lawyer,
11 perhaps getting less advantageous credit card offers.

12 Where does the self-reg fit in that scheme?
13 What are you -- given your position in the industry --
14 what's your explanation for that particular scenario,
15 understanding you don't have any of the facts other than
16 what was observed?

17 MS. FITZGERALD: Exactly. I have no facts, but
18 I --

19 MR. OLSEN: But I think you can see the web site
20 has a particular demographic, and there are particular
21 ads being delivered.

22 MS. FITZGERALD: Sure.

23 MR. OLSEN: Something is going on in the machine
24 somewhere. Where does the self reg kick in there? Is
25 that anecdote potentially harmful, troubling, concerning

1 to you? Is there a role for self reg there that would
2 address that scenario?

3 MS. FITZGERALD: So, as you clearly stated, I
4 don't have all the facts, and there's a lot more
5 questions that I had just listening to the bits that they
6 had that could, in my mind, explain some of the
7 variations, things like how much does the actual ad space
8 cost? Are the publishers charging different amounts for
9 different ads? And some of those advertisers may not
10 want to pay that different charge. Maybe they have
11 different volumes, whatever.

12 There are many, many, as far as I'm concerned,
13 factors that could be involved there. If there was an
14 advertiser that was not using those services for
15 marketing services, which is what my industry does, what
16 my company does -- we only use data for marketing
17 purposes, period. We don't use it for any of those --
18 and yes, we do have in our contracts you cannot use it
19 for any of those prohibited reasons like FCRA, and we do
20 check and see how people actually use it.

21 But, in my mind, self-regulation says if you're
22 part of this industry, if you want to be part of these
23 groups, we are going to use the data in a responsible
24 way. We are not going to try and violate anybody's
25 rights. But we're only going to use it for marketing

1 purposes, because in the end, it's an advertisement.

2 It's the same thing you get on TV. It's an
3 advertisement. You can either take it or leave it. If
4 you want a different offer, go to a different bank. You
5 don't like that bank or you want to see if the bank has
6 something else to offer, go talk to the bank.

7 So, there's many choices if you're marketing.
8 All these are are offers. We don't do things that are
9 going to give you credit.

10 MR. OLSEN: Okay. So, given that, it was simply
11 the delivery of ads? It doesn't present an issue that
12 the self-reg guidelines or --

13 MS. FITZGERALD: Yes.

14 MR. OLSEN: Does anyone want to address that or
15 comment on it before we move on?

16 MR. CALABRESE: I guess I'm a little skeptical.
17 I'm not sure this is directed at self reg, but I'm a
18 little skeptical of the idea of it's just marketing,
19 actually gets you all the way to where you want to go.
20 One of the things, Commissioner Brill's concurrence to
21 the recent data broker report, she talks about the use of
22 aggregated credit scores.

23 I'm not entirely sure I understood what that
24 actually means, given what I understand how a credit
25 score works. But the idea is that you're averaging

1 credit reports in 5 to 10 households in a specific
2 geographic area. I presume that you are using those for
3 things like marketing and determining what kind of ads
4 you are going to share with people.

5 To my mind, if, given the segmented and
6 personalized nature of today's internet, if we are
7 replicating the geographic segregation in our society and
8 people are seeing, based on what neighborhoods they are
9 in, different types of ads and offers, that is
10 problematic, full stop.

11 Even if they can go to another bank, if all they
12 are seeing are the crappy credit card offers again and
13 again -- and maybe because they, you know, are the kind
14 of people who go and get the only advertisement they see,
15 they don't know to go to another bank. They think that's
16 the bank, those are the offers they get.

17 So, to my mind, that kind of stuff is where a
18 market failure exists, where the CFPB should push harder
19 to see if those offers are actually dissuading people
20 from getting credit or if they are ending up with worse
21 credit offers because of them. So, that's, I think, an
22 area to push.

23 I just don't think the industry self-regulatory
24 model can fix that. Now, aggressive regulation may be
25 able to, but I just don't think that saying it's just

1 marketing is sort of enough to answer those kinds of
2 criticisms.

3 MR. OLSEN: Jeanette, did you want to respond to
4 that? You don't have to.

5 MS. FITZGERALD: Am I allowed to?

6 MR. OLSEN: It's totally up to you. Yes, I
7 invite you to.

8 MS. FITZGERALD: Well, my comment to that would
9 be, number one, not all advertising is about credit
10 cards, okay.

11 MR. CALABRESE: True.

12 MS. FITZGERALD: And not all advertising is
13 determined based on aggregated credit score, which I'm
14 not really sure I could tell you that either. I've
15 learned about zip plus four, but I haven't learned about
16 aggregated credit scores. We try to stay out of the
17 credit because we don't want to do any of that, even with
18 the banking clients that we have. We're just marketing.

19 But it's the same theory that if I live in an
20 apartment, somebody who is advertising lawn mowers
21 doesn't want to waste their money and their time sending
22 information about lawn mowers to me because I live in an
23 apartment. It's the same sort of activity that's going
24 on, at least from our standpoint.

25 MR. CALABRESE: I'm sorry, it's just not. If

1 you were looking at the credit scores of different people
2 in the apartment and aggregating them, which means if Dan
3 has got much better credit, and Chris has got much better
4 credit, and I've got worse credit, and I am bringing them
5 down, and they are getting worse offers, that is not the
6 same thing. It's not the same thing as where they are or
7 whether they can mow a lawn. It's different.

8 So, if these practices are occurring, and I hear
9 a lot of well, I haven't heard anything that's happening,
10 this is happening. It's been demonstrated. It's up to
11 the regulators to tell us how it's being used so that we
12 can see if it's got this pernicious effect.

13 Sorry I interrupted you. I apologize.

14 MS. FITZGERALD: It's okay.

15 MR. OLSEN: Dan, did you want to say something?

16 MR. CASTRO: I just wanted to say you started
17 the question by saying where are there market failures.
18 So, of course, I don't disagree that that could happen,
19 but the question is, is that a market failure. If the
20 three of us were living together in an apartment and
21 we're getting --

22 MR. CALABRESE: Separate apartments.

23 MR. CASTRO: Separate apartments. Just to be clear.

24 MR. CALABRESE: I'm just too
25 old to share.

1 MR. CASTRO: I was thinking three bedrooms.

2 MR. CALABRESE: Right.

3 MR. WOLF: Or, as they would say on Seinfeld,
4 not that there's anything wrong with that.

5 MR. CASTRO: So, if we're sharing an apartment
6 building --

7 MR. CALABRESE: Right. That was actually my
8 point.

9 MR. CASTRO: So, but the point here is, though,
10 what is going to happen over time, right. Because the
11 question is, you know, if I'm getting worse offers or
12 you're getting worse offers, then there's a market
13 opportunity there, right. So, there's an opportunity for
14 another company to come in and steal this business.
15 That's something good. I mean, that's the kind of
16 innovation we want to see. So, that's not a market
17 failure; that's a market opportunity.

18 So, if we're talking about what's going to
19 happen in the future, this is the panel that's looking
20 forward, I would say in your situation, we're going to
21 have market opportunities where companies have the
22 opportunity to come in with better data and solve these
23 types of problems.

24 MR. SPADEA: Actually, you are seeing that.
25 You're seeing, for example, traditional large financial

1 institutions are stepping back a little bit from low-
2 income areas with their providing financial services.
3 But at the same time -- well, it's not enough yet, in my
4 opinion -- you see community banks stepping in and
5 helping trying to serve those where the large banks are
6 pulling back.

7 Also, you see again, when I think back to
8 Chris's point, where you can see big data being part of
9 the answer. You see start-ups coming up with and looking
10 at alternative data points to better determine who is a
11 good credit risk. So, big data is also part of the
12 solution, I think, to the potential problem that you're
13 outlining. Again, I think you do see the market
14 responding to the problem that you pointed out.

15 MR. OLSEN: Michael, let me ask you a question
16 about something you said earlier on in your first answer.
17 I think you had mentioned that it's premature to
18 determine whether market failures exist, where there are
19 regulatory gaps. I think you said, and obviously you'll
20 correct me if I'm wrong, that more work needs to be done
21 to define harms, to figure out what is harmful, which is
22 a theme I think we've heard several times today.

23 So, I would just posit this question to you. If
24 more work needs to be done to figure out what is harmful
25 or, to put it another way, what is inappropriate, what is

1 unethical, if more work needs to be done there, what are
2 companies doing today in this state of uncertainty? Are
3 they being cautious? Where are their guidelines for how
4 to act in terms of appropriateness, ethical behavior, or
5 fairness?

6 MR. SPADEA: I would change the question slightly
7 about the uncertainty part to call it, and I think it was
8 pointed out earlier, a very, you know, nascent industry.
9 It's brand spanking new, really. I think everybody is
10 trying to feel their way along about the risk benefit,
11 what's ethically appropriate.

12 I think we need to hear more from economists as
13 to, you know, the risk benefit analysis. What is the
14 economic impact that new regulation may have? Will it
15 promote trust unless there's a benefit there? What is the
16 economic benefit or loss to consumers who have to spend
17 time trying to remedy inaccurate information?

18 What's the drain there from time, money? For
19 middle class families, it's not as much, but when you
20 think of low-income families that are wage earners taking
21 a day or two off to deal with something like this, that
22 could have a very dramatic impact on them.

23 I think we need to hear more from ethicists and
24 try to look at, you know, what can be taken in from --
25 institutional review boards were mentioned earlier. Is

1 there some good practice there that can be pulled in?
2 How do we look at harm in those situations? More from
3 ethicists in general to help us figure out, you know,
4 what's right and wrong. Should there be -- harm include
5 things other than just economic harm as well?

6 I'm not necessarily advocating or arguing
7 against any of these, but it feels to me that harm is
8 really critical because companies need clarity on what
9 are the risks that they should be acting to mitigate.
10 Without that clarity, it really just -- you know, it's
11 hard to coalesce around a series of best practices.

12 MR. OLSEN: I think you teed up Chris's --

13 MR. WOLF: Well, actually, before I get to the
14 FPF ADL report --

15 MR. SPADEA: I did that on purpose.

16 MR. WOLF: -- I just wanted to add to what
17 Michael said, because recently the Berkeley Information
18 School folks asked 40 thought leaders what big data was,
19 and there was 40 different answers. I think the one
20 slightly negative comment I will make about some of the
21 discussion today is we're painting with an awfully broad
22 brush in talking about big data and talking about harm as
23 the same thing in all contexts.

24 This really builds on what Michael said. I
25 think we have to look at it on a case-specific basis. If

1 there's predatory lending, predatory financial practices,
2 that's one area to look at. If there's use of big data
3 inappropriately to categorize people because of their
4 medical conditions, that's another area. If it's for
5 advertising versus actual financial offerings or credit
6 scores, those are all different things. I think we have
7 to consider these issues separately.

8 So, to help do that, the Future of Privacy Forum
9 just published something called Benefit Risk Analysis for
10 Big Data Projects, which tries to provide a framework
11 that can be used across the 40 or more instances of big
12 data and the many potential uses and harms and really
13 moves privacy impact assessments forward to talk about
14 data benefit analysis.

15 So, I commend folks here and those watching to
16 take a look at some of the work that my colleagues, Jules
17 Polonetsky, Omer Tene, and Joe Jerome have done.

18 MR. CALABRESE: Can I offer a countervailing
19 report? I've read Chris's report. I think it's very
20 good. Everyone should also then read David Robinson's
21 report, which I think also tackles very specific and
22 concrete examples and I believe takes a little bit of a
23 more critical view of some of the areas.

24 Everybody in the civil rights community agrees
25 that data is a good thing and can help things. But David

1 talks a little bit about some of the complexity of
2 algorithms. So, it's David Robinson's report. Sorry, I
3 just thought I'd balance it.

4 MR. OLSEN: That's fine.

5 MR. CALABRESE: They're available as a box set.

6 MR. OLSEN: Chris Wolf, one follow-up question
7 on your big data risk benefit analysis. Are companies
8 engaged in these sort of activities today, do you know?
9 Are they undertaking a sort of risk benefit analysis
10 today? If not, why not? If we think it's a good idea
11 for them to do that, how do we go about --

12 MR. WOLF: Obviously, I can't speak for all
13 companies. I can tell you from a very unscientific
14 sample of the clients that I advise that they are,
15 because either based on my advice or because they came to
16 the realization on their own. They understand that they
17 are under the spotlight with respect to the use of data
18 by advocates, by regulators, by the media, and, of
19 course, by consumers.

20 So, there is a new era of transparency that I
21 think we can all applaud and embrace, the fact that we're
22 here and we're talking about these things, and the fact
23 that it is in kind of the public policy consciousness. It
24 means the companies understand they have to do it
25 correctly. This isn't the wild, wild west, and they have

1 to behave responsibly and do the kinds of use analyses
2 that reflect an ethical, moral, as well as, of course, a
3 legal judgment.

4 MR. OLSEN: Okay. How public are those
5 analyses?

6 MR. WOLF: Well, often they're not because often
7 they reflect business strategies and trade secrets and
8 products in development. So, I don't think you can
9 expect them to be public.

10 MR. OLSEN: So, you mentioned transparency. How
11 do we solve the transparency issue if these sorts of
12 analyses are not transparent?

13 MR. WOLF: So, this room is full of lots of
14 different kinds of people, but among them are the
15 corporate representatives of a lot of the folks that I'm
16 talking about. There's a big privacy public policy
17 community. The IAP Privacy Academy is taking place in
18 San Jose later this week. Completely sold out. Believe
19 me, there's plenty of discussion about how to do this
20 better, how to do the cost benefit analysis better and a
21 lot of information sharing. I don't think you can ask
22 much more from companies about that.

23 MR. OLSEN: Jeanette, what are you seeing? Is
24 that something that Epsilon does, this sort of cost
25 benefit analysis?

1 MS. FITZGERALD: Absolutely.

2 MR. OLSEN: And just to key off my earlier
3 question, I think there was discussion at one of the
4 earlier panels, I can't remember which one, but I think
5 it was danah boyd who said, you know, there's a lot of
6 public uses of data and data sets that are very
7 transparent, how the data is crunched, how the data is
8 analyzed, what the results are. All of that is made
9 public. There is no similar transparency on the
10 commercial side.

11 I think the cost benefit analysis, the benefit
12 risk analysis, sounds like something responsible
13 companies should be doing today. The question is, how
14 does anyone get any sort of comfort that the analysis is
15 either not affected by concerns we would care about or
16 the results aren't unfairly impacting someone? How do we
17 get over that transparency hurdle?

18 MS. FITZGERALD: So, there are a couple things.
19 One is, certainly how we look at any new products or how
20 we continue to use products has evolved over time because
21 this notion of privacy and how society accepts it has
22 evolved over time. The privacy profession hasn't been
23 around that long when you look in the scheme of things of
24 how long businesses have been operating. Nobody really
25 thought about it that much.

1 So, it's evolving now. As Chris Wolf said, the
2 IAPP, it sells out all the time. There's always people
3 that are -- I see the same group all the time, but we're
4 all talking about new issues as it evolves. If we, as a
5 company, my company, for example, Epsilon, decided to
6 tell everybody exactly how we did a risk benefit
7 analysis, that would be giving up trade secrets. We're
8 not going to do that. Other companies are going to feel
9 the same way. That's part of our "special sauce" to make
10 it.

11 Now, that doesn't mean that if there was an
12 impact that somebody felt was discriminatory, that
13 somebody is not going to come back to us and say, you
14 know, there's a problem here. Then, what happens? Our
15 name shows up somewhere. We don't want our name to show
16 up. So, there's a lot of good reasons why we're very
17 careful about those things.

18 Our team looks at things like if you were a
19 consumer and you had given your data in this first
20 instance, for whatever reason, would it make sense to
21 them that they would be using it this way later? Now,
22 some of it is, you know, complementary and you can figure
23 out okay, it makes sense. Some of it is so far in left
24 field you just have to look at your team and say, I get
25 what you're trying to accomplish, but this ain't going to

1 work. Not going to do it because we can't explain it
2 later and do it with a straight face.

3 MR. OLSEN: Okay.

4 MS. FITZGERALD: I mean, the fact that there's
5 hearings, the fact that there's a huge group of people in
6 the public, and a lot of them are sitting around here,
7 who will come and look and tell you you're doing
8 something wrong, is pretty good at, you know, making sure
9 that you do the right thing.

10 MR. OLSEN: Does anyone else want to offer
11 anything on the transparency concept? How do we improve
12 the state of transparency of data use or analytical tools
13 or algorithms today?

14 MR. CALABRESE: I would like to. I think we're
15 sort of woefully inadequate when it comes to transparency
16 right now, so I'll pick on the data brokers just because
17 there was a recent report. There's a fair amount we know
18 about exactly what their practices are.

19 In the recent FTC report, I believe it was
20 Acxiom, they said Acxiom had something like 1,500 or more
21 than that data points on every consumer. I went and
22 looked at my Acxiom profile. There's nowhere near 1,500
23 data points about me, nor, and I think more importantly,
24 is there anything about how they're being used, like sort
25 of what score or assessment am I being offered.

1 Am I being grouped as an urban scrambler? Am I,
2 like, a vulnerable consumer? In my personal life, I'm
3 very vulnerable. But until I know those assessments, and
4 I get that it's special sauce, but the individual
5 consumer should be able to know if they're being targeted
6 or there's an assumption being made about their health,
7 their finances. So, that's the kind of transparency I'd
8 like to see more of.

9 MS. FITZGERALD: So, let me throw one thing out
10 in response to what you're saying that Acxiom does.
11 Epsilon, too, has a site, a section within our site, I
12 don't know whether it's called a microsite or not,
13 because I'm never even sure what those are, where a
14 consumer can go and we give them education about how
15 their data is used for marketing purposes, places they
16 can go with the DMA, places they can go to the FTC to get
17 further information. They can go to a couple different
18 other sites that will give them lots of information about
19 how it's used. I don't know how many people are actually
20 going to go read all that stuff. It takes a long time to
21 slog through it because we all did before we put it up
22 there.

23 But the other thing it does is it says, look, if
24 you want some information about you, if you want to know
25 what kind of information we have about you and what group

1 we put you in, you have to send us something because at
2 this moment we haven't figured out the right way to do it
3 online. I've got a couple ideas, but I don't like what
4 I've seen so far, because we don't have credit cards, we
5 don't have driver's licenses, we don't have social
6 security, and I'm not going to ask for those to then give
7 you a report. That seems like counterproductive.

8 But we can give you a report, and I should have
9 brought it. I'm sorry I didn't. But basically, it says
10 your name, your address, whether you have kids in your
11 house, whether you own your home, and then some of your
12 interests. So, we like to be outdoors. Yes, we do hunt
13 because we're in Texas. Fish.

14 And then, it says at the bottom you're in this
15 group, and it says these are the basic characteristics of
16 this group. The salary is about this, you buy books and
17 magazines, you shop online. I can't remember what the
18 other ones are. But, I mean, that's available. You can
19 go get that and we'll show you. Frankly, after you read
20 that, if you're really still worried, we'll opt you out.

21 MR. CALABRESE: I appreciate it. I've seen some
22 of it. I don't think I've ever been to yours, but I also
23 don't see the same alignment when I read about what
24 regulators are writing about this industry. That makes
25 me wonder where the disconnect is. And maybe it's a

1 classic. We've got good actors and bad actors. Somebody
2 brought that up, too, which, of course, is the classic
3 argument for regulation. The good actors are already
4 behaving properly, and the bad actors aren't going to do
5 anything unless you regulate them. But I do see a
6 disconnect in the transparency.

7 MR. SPADEA: If I could, just briefly, I don't
8 know if the answer is more transparency but perhaps
9 better transparency. We've all heard about the studies
10 where, you know, it will take you 29 years or something
11 to read all the privacy policies. It's not because
12 consumers can't do it if they want to; it's just, who has
13 the time to do that.

14 If we inundate consumers with descriptions of
15 the technologies and the business processes and all the
16 data flows, they're not going to read past the second
17 privacy policy. Think about when you buy a new computer
18 and reinstall your software and reupdate the stuff from
19 the cloud. You're not reading all that. I don't read
20 all that.

21 More transparency is just going to dull the
22 senses, which I think is what you're seeing a little bit
23 with the breach and notification piece. If you think
24 about the airline industry, you don't go on to the
25 website and it doesn't show you how many hours the pilot

1 slept, where the maintenance records are for the
2 airplane, no. Those are not the factors that you're
3 looking at when you make the purchase.

4 You want to deliver the critical information at
5 the moment in time and that's that. Perhaps a better
6 approach may be, which we all do in some ways, you know,
7 risk rate the data for that data that's most sensitive,
8 that might have the most potential impact. There's a
9 higher, you know, notice requirement there. But just a
10 blanket across the board, dump tons of more information
11 on consumers, I can't see that as protecting consumers.
12 In fact, it may put them at more risk.

13 MR. OLSEN: Michael, I don't disagree with that.
14 I think in terms of transparency, there are a variety of
15 ways to deliver that. I think what I was contemplating
16 is some mechanism for companies -- I think Peter Swire
17 alluded to this in the last panel -- if there is an
18 unfair practice, if there's unfair marketing going on,
19 you could foresee a scenario where the business has a
20 justification for why it engaged in the particular
21 marketing campaign.

22 It's not necessarily a justification for
23 consumers; it could be a justification for a self
24 regulatory governing body like DMA. It could be a
25 justification for regulators. It's not necessarily

1 giving a notice to consumers every time they receive an
2 ad that says this ad was delivered based on the following
3 15,000 analytical data points. I don't see that as being
4 particularly helpful.

5 But I think if there is a concern about how data
6 is being sliced and diced and crunched and whether there
7 is something going into the analysis that is of concern
8 or something coming out at the end, that raises questions
9 about the transparency of the analysis itself.

10 So, Jeremy, and Dan too, but Jeremy, I'd like to
11 ask, is there a role for technology, for example, in
12 helping address some of the transparency issues or some
13 of the concerns about whether there's something of
14 concern happening behind the curtain?

15 MR. GILLULA: I mean, I certainly think so. I
16 think the technology can help a lot. I mean, going to
17 what you said about, you know, you don't necessarily need
18 to show every consumer, you know, exactly how they got
19 this ad, unless maybe one or two consumers or, you know,
20 some consumers who are concerned are interested. Then,
21 you know, if there were a way for them to click on a
22 little part of the ad that said, hey, yes, this is why we
23 served it to you.

24 So, it's not that, you know, everyone always
25 gets it all the time, but so that people who are

1 concerned can try and understand. So, someone like Dr.
2 Sweeney, when she's doing her investigations, not just
3 say okay, this is what we saw, but hey, and this is why
4 the ad companies say they gave it to us. I think, you
5 know, through a little bit of disclosure through the --
6 it's not a technologically infeasible thing to try and
7 do.

8 In terms of also just using technology to
9 determine when discriminatory things are happening, it
10 also occurs to me that, you know, in some way, and I
11 don't know if this is the sort of thing that EFF would
12 take on, but, you know, people could turn big data back
13 on the data brokers. You could think of a browser plug-
14 in that collects the ads that you're seeing. Then, if a
15 lot of people install that, then you can start comparing
16 what ads different people are seeing.

17 So, in some way you could sort of essentially
18 collect big data on big data and then try and do some
19 open source analysis perhaps. I think the reason that
20 something like that might be valuable is because a lot of
21 times these sort of effects aren't necessarily obvious,
22 because most of the time I don't know what ads Michael is
23 seeing. I don't know what ads Jeanette is seeing. I
24 just know what I see, and I just assume it's normal. I
25 assume there's nothing, you know, discriminatory going on

1 with it. Until people can start to compare these things,
2 I think a lot of this will sort of be shadowy and not
3 very transparent.

4 MR. OLSEN: So, I want to come back to the
5 technology in a second, but I want to let Dan jump in
6 here.

7 MR. CASTRO: Yeah, actually, going off of what
8 Jeremy said, I do think big data is a solution here to
9 many of these types of transparency things. In fact,
10 what you're describing, for example, is the True Car
11 model, right, where it's a company that collects all the
12 data from car dealerships about what prices people pay.
13 If you want to use them, then you get to find out what
14 other people have paid. You share your data and that's
15 maybe a less discriminatory way of buying a car. You
16 know you're not getting sold based on, you know, the type
17 of shoes you're wearing when you go to the dealer. So,
18 there are lots of ways that you can use this.

19 This gets to a really important point about
20 whether, you know, the discrimination or harm that you're
21 positing here is something that's intentional or
22 unintentional, which is something that the first panel
23 talked a lot about. How you address those might be
24 different, so you need to think about which type of
25 problem you're trying to address.

1 If it's, you know, unintentional harm, you
2 really do have to address a lot of that through data
3 analysis. Nobody is intending to do it, so you have to
4 make sure you have smart data scientists doing things
5 consciously, but also that you're able to evaluate
6 outcomes. If it's intentional, then you have a human
7 problem, and maybe you address that differently.

8 The second point here is really about, you know,
9 whether or not you want to open up these algorithms,
10 because I think that's really important when you start
11 thinking about the trajectory of how innovation will
12 occur in this space. Ultimately, I think the goal is to be
13 that you're innovating around accurate data so that the
14 innovation is really in the algorithms.

15 If you look at the open data movement, that's
16 what this is all about, right. It's not about who has
17 the data, which is the kind of world we live in right
18 now. That's why we have data brokers, because you can
19 buy data. It's really valuable maybe what data you pay
20 for.

21 What you really want to get to, I think, is
22 where getting access to the data is really easy and it's
23 all the intelligence and innovation that you build on top
24 of that that's hard. So, you want to promote that. So,
25 I think part of that is by allowing trade secrets to

1 exist, is by allowing, you know, intellectual property to
2 be protected here.

3 So, as we think about regulation to address this
4 issue, I think we have to consider what this data science
5 space will look like in the future. Part of that will be
6 accurate data, so the question then will be, you know, do
7 you want innovation in algorithms or not.

8 MR. CALABRESE: I was just going to say, this is
9 hard. Take the e-Verify example. E-Verify is a
10 government system for essentially deciding whether you
11 are going to get a job. The goal is to say if you are
12 lawfully in the United States, you're work eligible. You
13 query this government database, right. If you're not,
14 the employer isn't supposed to hire you.

15 Well, this database has been in existence and
16 being perfected since 1996, right, so a very long time.
17 It uses fairly homogenous data. It's all government
18 data. It's all a relatively discrete set of data sets.
19 It still has an error rate that is 20 to 30 percent
20 higher for certain classes of people who are in this
21 country legally but are immigrants.

22 So, this is a system that is run by the
23 government with oversight that still has substantial
24 errors. So, I didn't mean to make too much of a point,
25 but this is really difficult to do. I think that we need

1 to acknowledge maybe that some of our uses, especially if
2 they're going to result in things like people not getting
3 jobs, like, until we have a high degree of confidence
4 that we're actually doing this right, maybe we shouldn't
5 be allowed to do it. I know that's a little bit anathema
6 but --

7 MR. WOLF: I think that's the throwing the baby
8 out with the bath water problem that I was talking about,
9 because the point of the FPF ADL report -- and for those
10 who don't know, the Anti-Defamation League was founded
11 100 years ago to combat antisemitism and promote justice
12 and fair treatment for all. The Future of Privacy Forum is
13 a privacy think tank. We came together like Reese's
14 Peanut Butter cups to put something really good together
15 by combining both our missions.

16 So, we looked at things, for example, like the
17 Urban Institute, which recently combined public school
18 data with demographic information to show segregation in
19 public schools, use of big data to identify a problem
20 with discrimination. In another example, the National
21 School Board Association supplemented the Department of
22 Education research with raw census data to also show
23 disparities and the fact of school disciplinary practices
24 on the graduation rates of various minorities.

25 We've seen big data used to fight discrimination

1 in the workplace. Somebody mentioned earlier this
2 company Entelo, which produces a digital recruiting tool
3 for those companies who want to have a more diverse
4 workplace. It helps them use big data to identify
5 prospects.

6 In another example, Google has used big data to
7 identify problems in its own hiring process. It's a real
8 credit to the company because it admitted that its own
9 brain teaser interviews apparently unfairly favored
10 males. So, it's now reformed its hiring practice after
11 making that realization to evaluate candidates without
12 questions that may unfairly disadvantage one gender.

13 We see the EEOC using something called FedSEP
14 which is an electronic portal through which 325 agencies
15 now report workplace discrimination charges. Those
16 numbers are crunched in various ways. So, we have 14
17 examples in our report of how big data --

18 MR. OLSEN: Right, and those are great examples.
19 I think they all serve to really demonstrate that big
20 data has tremendous societal value.

21 Let me first jump in here for a second. I think
22 what we're talking about, I think, Chris, maybe you and
23 others on the panel, are teeing up the scenario of
24 regulation versus no regulation, law versus no law.
25 That's certainly an option. Should we have another law?

1 Should we recommend legislation? Should congress pass
2 legislation? That's an option.

3 We all know how challenging it is for something
4 to come out of congress. So, let's talk about best
5 practices. Are there practices that companies can engage
6 in that would measure, or cabin, or restrict, or evaluate
7 potentially harmful uses that they're not going to
8 impact potentially beneficial big data uses?

9 I mean, if you have a data ethicist or a chief
10 fairness officer, you know, that person and the
11 evaluation that that person undertakes before a new
12 program is rolled out, it's not going to curtail the
13 benefits of big data.

14 MR. WOLF: No question about it. I love this
15 quote from a report that KPMG recently did. They said
16 "organizations that attempt to implement big data
17 initiatives without a strong governance regime in place
18 risk placing themselves in ethical dilemmas without set
19 processes or guidelines to follow. Therefore, a strong
20 ethical code along with process, training people, and
21 metrics is imperative to govern what organizations can do
22 within a big data program."

23 MR. OLSEN: Okay. How do we come up with a
24 strong ethical code?

25 MR. WOLF: So, I have lots of booklets to waive

1 around, but I come back to the original one, which is the
2 benefit risk analysis for data projects. Having a
3 framework and a methodology and a discipline within an
4 organization is absolutely essential.

5 Now, is it like a traditional IRB? Maybe not,
6 but Professor Ryan Calo has said that it's certainly
7 something to think about as a way to if there is a gap,
8 fill the gap. But even if there's not a gap, to avoid
9 adverse consequences.

10 MR. OLSEN: Jeremy, you wanted to jump in?

11 MR. WOLF: I was actually going to sort of
12 address the question to Christopher. It sort of goes
13 back to what you're saying, that we're painting big data
14 with a very broad brush. It seems to me the difference
15 between what you're talking about and what Christopher
16 Calabrese was talking about is he's talking about uses of
17 big data where a decision is made about an individual.
18 Every single positive use of big data I've heard so far
19 today is we discovered something about a population.
20 It's not, you know, we decided to classify someone.

21 MR. WOLF: That then benefitted individuals to
22 allow them to have an education free of discrimination or
23 healthcare free of discrimination.

24 Mr. GILLULA: Sure, absolutely. But, you know,
25 that's called science. Just that we have more data or we

1 collect more data, we can find more things. But what
2 we're talking about, a lot of the harms, are harms where
3 data about a person is then used to make a decision about
4 that person, not we found some trend and then we adjusted
5 our methods.

6 We found some trend and then Google decided, you
7 know, yes, we need to change our hiring practices.
8 Google looked at your data when, you know, they were
9 deciding whether or not to bring you into an interview
10 and based on the data decided not to bring you in.

11 MR. SPADEA: I disagree with that
12 characterization. He gave examples where people benefit
13 in the end. Your examples or Chris's examples was
14 talking about harm to individuals. It's called the risk
15 benefit. We look at, you know, what the potential risks
16 are, the potential harm, and we weigh it against the
17 benefit. You can't answer the question you're posing
18 without the bringing of the two together. So, I would
19 say, no, they are apples to apples, not apples to
20 oranges.

21 MR. CALABRESE: Yes, but it's easy when the
22 benefits are to the company and the harms are to the
23 person. It's, like, yeah, great. I don't want to be the
24 guy on the harm's side. That's why we need government
25 standing here saying, that's not okay. This data isn't

1 accurate enough. This is harming people, and you didn't
2 give this person a job.

3 MR. WOLF: But, Chris, you're assuming that it's
4 uniformly harmful to the consumer. No one has said that.

5 MR. CALABRESE: I'm not assuming.

6 MR. WOLF: No one has said that today.

7 MR. CALABRESE: I'm assuming that you need a
8 framework in place, backed by something more substantial than
9 self-regulation, to make sure that the harms are as mitigated
10 as possible and do not fall on particular classes of
11 people or individuals.

12 MR. SPADEA: You're assuming that if a benefit
13 is provided by a private company, that there's something
14 wrong with that. That doesn't equal to an actual
15 benefit. That's what, at least, it sounds like I'm
16 hearing.

17 MR. CALABRESE: What I'm saying --

18 MR. SPADEA: Let me just finish one thing. I
19 was going to add, though, I do agree to your point where
20 there is harm, you know, there should be some type of
21 remedy. We shouldn't just leave consumers floundering.
22 The question was, do we need a law or not. I think what
23 I'm trying to say is that the evidence to say that we
24 need legislation now is not there.

25 As this industry continues to develop and we

1 have more information about harms, about benefits, we
2 need to continue having this discussion, and there may
3 come a point where we do need further regulation or
4 legislation. But we need more information. We should
5 start with the least interventionist approach. If that
6 doesn't work, we ratchet up the intervention.

7 MR. OLSEN: I guess the question I would ask
8 before I turn it over to Dan goes back to the
9 transparency question. If there is no transparency about
10 how the data is being used, then how do we get to the we
11 have more information point in order to make a decision?
12 It may be that companies internally know how they're
13 using the data, but they're the only ones who know that.

14 So, Dan, you wanted to --

15 MR. CASTRO: I think this would be a good point
16 to talk about this paper that we released last week.

17 MR. CALABRESE: Everyone else did.

18 MR. OLSEN: Let's bring the level down a little
19 bit.

20 MR. CASTRO: Since you brought it up --

21 MR. SPADEA: It's the afternoon panel.

22 MR. CASTRO: We released a paper called the Rise
23 of Data Poverty in America. This gets to what
24 Christopher was talking about, which is, you know, what
25 are the individual benefits and risks. So, the point of

1 this paper, we went through and we talked about specific
2 benefits that individuals are seeing in areas like
3 healthcare, education, and financial services.

4 We also talked about the challenges that we've
5 had in the past, both in terms of the digital divide and
6 how that might translate into a data divide, as well as
7 challenges that we've had in small data sets. So, you
8 know, the best example of this is in healthcare where
9 historically, if you look at, for example, clinical
10 trials, minorities and women have been underrepresented
11 in this data. Just as when we're talking about big data,
12 decisions are made from big data, decisions are made from
13 small data as well.

14 So, decisions have been made in the past, for
15 example, by the FDA about what drugs and treatments were
16 safe and effective. It turned out that, of course, once
17 they release it to the full population, that population
18 didn't match up with the clinical trial population. Some
19 things were unsafe.

20 So, the questions we asked in this report were,
21 you know, what challenges might, you know, certain
22 disadvantaged communities see if there are, in fact, data
23 gaps, if there are, you know, data rich communities and
24 data poor communities. We actually looked at Wikipedia
25 contributions on a per capita basis. We tried to do kind

1 of an initial mapping of what data deserts might look
2 like in the United States.

3 There are these really interesting gaps. So,
4 the questions are, as we're using all this data, and I
5 think that's generally good, are there populations that
6 are left out, and what do you do? So, if you compare
7 what we've done with the digital divide, we don't say,
8 oh, some people don't have access to computers, let's
9 stop using computers, right. That's kind of the message
10 I hear sometimes today on the panel, which is that you
11 don't want to use data. That's not the answer.

12 The policy answer to that type of problem of a
13 data divide is to say how do we make sure that
14 disadvantaged populations also have data available about
15 them, that they can share in these benefits. When you look at
16 it, it's very clear that there are huge, you know, economic,
17 educational, health benefits. We want to make sure all
18 of these groups can share in that.

19 MR. OLSEN: Yeah, that brings up a good point. It
20 reminds me of the street bump example where data was
21 being collected about road conditions from smart phones.
22 There was a question about how broadly representative
23 different communities were in that data collection.

24 I could see something similar happening with
25 wearables. If policy decisions on health data are made

1 based on input from wearable devices, are there certain
2 communities of people that are being excluded, which
3 again sort of suggests that at some level, there's some
4 sort of fairness or ethical approach that has to be
5 applied as a frame for any of these data collection
6 practices.

7 MR. CASTRO: Brief response to that. I think
8 part of that is data literacy, not only among the, you
9 know, data scientists so they understand what exactly it
10 is they're doing but also policymakers who are
11 interpreting this data or interpreting the results.

12 MR. OLSEN: Correct.

13 MR. CASTRO: Hopefully, you know, we're doing
14 some of that today.

15 MR. OLSEN: Michael.

16 MR. SPADEA: In the street bump example, you
17 know, that's a great example of how you can get tripped
18 up. But it's also a good example, I think, of how you
19 can, you know, fix the situation. So, the answer would
20 be not, you know, to get rid of the app or anything like
21 that, but if you understand where the smart phone
22 saturation is and where it isn't, you can then put in
23 mitigating controls.

24 So, we know that in areas which will be
25 predominantly middle class or upper class, there's going

1 to be high smart phone saturation. Therefore, the
2 Department of Public Works is going to get really good
3 data on where all the potholes are, and they're going to
4 get fixed. But that's not going to happen in the lower
5 income neighborhoods. So, what do you do?

6 Well, you know you need to have something else
7 in place for those neighborhoods. So, you take the money
8 that you save from pulling DPW people on pothole patrol,
9 or whatever they do, you take some of them, you take half
10 of them and you just take that money savings and you put
11 it someplace else. You take the other half and just
12 throw them right into the neighborhood that doesn't have
13 that saturation. At the end of the day, you get to the
14 same place. You get there more cheaply. Everybody is
15 happy.

16 So, you can, where you know where a problem like
17 that exists -- and the key thing is the governance that
18 Chris talked about earlier. There should be a process to
19 spot those risks. The ethics piece comes in where, okay,
20 we now need to fix it. We can't just let that harm sit
21 out there. But we can still roll forward with the
22 application and, you know, with a private company,
23 generate revenue and service the consumer.

24 MR. OLSEN: Let me key off that and tee up a
25 question that we've been sort of hinting at during this

1 panel. There's a debate between a use base model of data
2 handling and a data minimization approach. I'll just
3 pose this question. There's been talk on various panels
4 today about data governance. Chris Wolf mentioned it.
5 You need to apply a data governance methodology. We
6 talked about making sure we have a clear idea of
7 fairness. We talked about having an ethical approach.
8 We've talked about how we're at the early stages of these
9 sorts of practices.

10 So, I put the question to the panel, if we
11 haven't resolved the framework for applying an ethical
12 construct to data practices or fleshing out harm the way
13 we need to, why isn't data minimization still an
14 important component of information handling practices?

15 MR. WOLF: So, maybe I can start. I referenced
16 the fact there are at least 40 different definitions of
17 big data, but there's one kind of fundamental
18 understanding. It relies on volume, variety, and
19 velocity of data that leads to unexpected discoveries.

20 So, how do you provide notice at the time of
21 collection to allow consumers to make choices about
22 discoveries that you don't know will happen? That's sort
23 of conceptually one of the problems I have with this idea
24 of a collection limitation.

25 But I think a more practical issue is one that I

1 think Pam Dixon very candidly acknowledged, is that there
2 are huge data sets already out there, structured and
3 unstructured, data exhaust, as she referred to it. Even
4 if we are able to minimize data collection or to provide
5 options that put limits on the collection, we're still
6 dealing with huge issues of use.

7 As we discussed here today on this panel and
8 others, consumers aren't simply going to take advantage
9 of the transparency options and make the choices that
10 perhaps we think they ought to. There has to be someone
11 responsible in the ecosystem. That's why, you know, we
12 urge the governance model and the focus on use without
13 rejecting the FIPP of collection, but without unduly
14 placing emphasis on it.

15 MR. OLSEN: Anyone else want to comment on this?

16 MR. CALABRESE: Yes. You'll be shocked to learn
17 that I think that use it not enough in and of itself. I
18 think data minimization has an important role. But I
19 guess I would put a plug in for all the FIPPs here,
20 right. I mean, the fact is that a lot of times consumers
21 don't take the time to know about what's being collected
22 about them because there's nothing in it for them. All
23 they can do is, like, learn about it and go, well, you're
24 out of luck, like you don't have the rights to do
25 anything with this information or limit it.

1 So, you know, I think that having both
2 minimization but also use limitations and the ability to,
3 for example, say, I'm going to keep my salary information
4 from becoming part of this data ecosystem because I'm
5 noticing that I'm not getting as good coupons and offers
6 because people think I don't make enough money to be
7 worth those good offers. I'm going to keep that
8 information to myself.

9 Now, if you have the ability to control various
10 types of information, I think you are much more likely to
11 learn how it's used and much more likely to endeavor to
12 be an active data user, at least about yourself.

13 MR. OLSEN: Anyone else on this particular
14 point?

15 MR. CASTRO: Well, just to a couple things that
16 have been mentioned here. I think we have to separate
17 between harms to an individual as in, you know, I'm
18 paying more than I'm paying today versus, you know, I'm
19 paying more than I'm paying today because someone has
20 something wrong about me, right.

21 Like the e-Verify example, if I can't work
22 because the government, you know, fundamentally has
23 something wrong about me, regardless of the law itself,
24 you know, that's a different problem than if my insurance
25 company charges me more because I speed a lot and now

1 they know about it.

2 We need to separate out those types of -

3 MR. WOLF: One is a harm and one is actually an
4 improvement because there's actually a benefit to somebody
5 else.

6 MR. CALABRESE: There's an information asymmetry
7 here, right. If I know that you are wealthy and
8 you are more likely to come into my store if I give you a
9 really robust coupon, say a \$15 coupon, but if I know
10 you're income, I don't have to give you a \$15 coupon. I
11 can get you in the store with a \$3 coupon.

12 Now, we can argue about whether that's a genuine
13 harm or not and you can shop somewhere else, but the fact
14 is that you know something about me and you're using that
15 to provide a differential in something that I would
16 value.

17 MR. CASTRO: But the point of that is, though,
18 you can do the opposite as a consumer. So, a great
19 example of this is if you look at, you know, car
20 dealerships. It used to be if you wanted to get a used
21 car and you didn't have many assets and you didn't have
22 any collateral, you weren't going to get a car. They
23 weren't going to make a loan to you. The reason is
24 because you would have a car and you could drive off with
25 it and stop making payments. There's this huge risk,

1 right. No one was going to do that.

2 Now, you know, using data, you can actually say,
3 okay, I'll have a GPS-enabled device. I will tell you
4 where I am. You can have this data about me so I will
5 prove that I'm not running off with the car. That way,
6 there's a significantly lower risk to you. Now you'll
7 make a loan.

8 So, you have all these dealerships that are now
9 making loans to individuals that they didn't have access
10 before. So, you know, if you're a single dad and you get
11 a job, you need reliable transportation, now you can do
12 that. That's the consumer using data for good. That's
13 what we want to see more of.

14 MR. CALABRESE: That's voluntary. I'm choosing
15 to give you that data in response to a need. I mean,
16 that's completely different than my unwilling disclosure
17 of my salary through a third party data broker. It's
18 apples to oranges.

19 MR. OLSEN: Let me turn to one point we've
20 touched on a bit earlier today and tee it up this way.
21 Data governance, seems like everyone agrees, is
22 important. Companies are moving towards more formal risk
23 benefit assessments, which seems like a good step. We've
24 discussed at length the transparency issue there. It may
25 not be visible how companies are applying the data

1 governance methodology.

2 So, should consumers consider other options that
3 exist or should we consider other options from a
4 technological standpoint? Should we push for data
5 tagging, for example, that would identify the provenance
6 of data elements, or are we beyond that? Or, should we
7 consider, you know, random identifiers that would mask
8 your identity as you navigate the web so that you appear
9 to be a new person every time you visit a particular web
10 site? Or should we entrust our data to a third party
11 with a permissions scheme? Are there measures consumers
12 can take or companies can deliver that would mitigate the
13 risk that the data would be used in harmful ways?

14 MR. WOLF: Unlike your first question, which I
15 refuse to answer, which is a yes or no question, the
16 answer to all of your questions is yes. I think
17 technology does have potentially a very significant role
18 here to play to provide exactly those kinds of
19 protections, exactly those kinds of options. You didn't
20 say de-identification specifically, but I think that was
21 implicit in your question about random identifiers. So,
22 you know, I think there's great hope in technologists.
23 They've certainly gotten a lot richer than lawyers.

24 MR. OLSEN: Even you, Chris?

25 MR. WOLF: Hey, that's private information.

1 MR. CALABRESE: I've seen those.

2 MR. OLSEN: Anyone else want to address it?

3 MR. SPADEA: I think it ties in nicely to the
4 reasonable or the responsible use, you know, viewpoint.
5 If you own it, if you have the data, you're responsible
6 for it. I would interpret that quite broadly. You're
7 responsible for, you know, who it's transferred to.
8 You're responsible to keep it, you know, secure. You
9 have to act in a responsible manner. Implicit in all the
10 risk mitigants that you just set out there, those would
11 all be tools in the toolbox of the organization to help,
12 you know, mitigate these risks. They need to act in a
13 responsible manner.

14 I would just add, I think actually the
15 responsible use viewpoint requires a strong and well
16 resourced regulator because they're the ones at the end
17 of the day that are going to really have to make some of
18 the terminations about what's responsible. I don't know
19 if this is true or not, but somebody from the FTC was
20 telling me that the FTC as a resource that, you know, today
21 is 50 percent less than it was in the 1970s. If that's a
22 true statement, I'm shocked.

23 So, I would say I really like the responsible
24 use. I think it ties in exactly to what you just said.
25 But the FTC needs a little more muscle to make sure data

1 is used responsibly.

2 MR. OLSEN: Anyone hear that who has the purse
3 strings?

4 MR. WOLF: Michael will be taking up a
5 collection at the door.

6 MR. OLSEN: So, we have, I think, just under
7 five minutes. I'd like to ask each of the panelists in
8 their closing make recommendations to anyone they want.
9 You can make a recommendation to industry, to the FTC or
10 other regulators, to congress, or to consumers. What
11 would you recommend are the next best steps to take as we
12 move into the world of increasingly complex algorithmic
13 analysis?

14 I'll start here, and we'll move down.

15 MR. CALABRESE: My recommendation would be that
16 regulators, specifically the FTC, but especially the
17 CFPB, very aggressively investigate whether the Equal
18 Credit Opportunity Act does reach some of these
19 practices, especially the marketing practices and the
20 marketing of credit offers, and whether the marketing of
21 higher credit offers to particular segments of the
22 population in fact discourages those populations from
23 pursuing credit offers and, hence, violates the Equal
24 Credit Opportunity Act.

25 I will do my own little plug and say that I

1 think the ACLU will provide more formal written comment
2 on this and encourage this before the close of the
3 comment period.

4 MR. OLSEN: Thank you.

5 Dan.

6 MR. CASTRO: So, I'd say, you know, I think this
7 is definitely the start of the conversation. We need
8 many more voices here. I think it's interesting.
9 Today's workshop has been fantastic, but, you know,
10 across town, there's a predictive analytics government
11 conference going on with some of the best predictive
12 analytics data scientists in the country, and they're not
13 in the room. So, you know, we need them here. They
14 certainly should be part of the conversation.

15 I guess my recommendation here is that, you
16 know, we really need to be thinking about the benefits
17 here. To me, if you care about discrimination, if you're
18 worried about healthcare or improving education for our
19 kids, the biggest risk is not how data is being used;
20 it's that we won't use it enough. We need to figure out
21 a regulatory environment and policy recommendations to
22 help encourage more use of data.

23 MR. OLSEN: Jeanette.

24 MS. FITZGERALD: So, I would say that we need to
25 spend time figuring out the best way to educate consumers

1 about the data that's being used on them, about them.
2 It's not just how it's being used, but we also need to
3 teach them that they can talk to the companies that have
4 their data. They can ask questions. Those people will
5 help them understand what information they have and how
6 it's being used.

7 I would encourage any other company that's been
8 thrown in the data broker realm that they, too, think
9 about ways that they can show consumers the information
10 they hold on them and how it's being used, what category
11 people fall in.

12 MR. GILLULA: So, I would build off what
13 Jeanette said. I do think that getting consumers
14 educated about these sorts of things would be a huge
15 benefit. I think part of that goes to the transparency
16 we've been talking about. I think it would actually be a
17 benefit for data brokers and marketers to be a little
18 more forthcoming about that sort of thing.

19 Right now, if you try to go and find this stuff,
20 it feels like diving into a deep and shadowy world. That
21 may not be what they mean it to be, but that's what it
22 feels like. I realize a lot of this is trade secrets,
23 secret sauce, but even just sort of giving general ideas
24 to consumers I think would be a huge benefit.

25 The other recommendation that I would make is

1 actually towards the FTC and really anyone sort of
2 observing this space. Look closer, look past the height.
3 I'm going to reiterate this point that I said earlier
4 because I don't think it was adequately addressed, that a
5 lot of the benefits that people tout about big data are
6 benefits that come from analyzing and learning things
7 about a population.

8 For every, you know, 10 benefits of big data I
9 hear about that, I hear maybe 1 about how individualized
10 targeting did big data help people. It's that
11 individualized targeting where I think a lot of the harm
12 is. I don't think there's a lot of harm in learning
13 about, you know, hey, look, these types of students need
14 help or these interviews are harming people. It's when
15 decisions affect individual people's lives that I think
16 we need to start thinking about.

17 MR. OLSEN: Michael.

18 MR. SPADEA: I would urge companies to develop
19 enterprise-wide risk programs. As part of that, have a
20 data risk framework. I think you could just simply read
21 all the papers that have been discussed or otherwise
22 provided today to come up with a list of the potential
23 risks.

24 You make determinations about what apply to your
25 organization, make determinations about where your risk

1 appetite is, and then put controls in place. While I
2 guess some of the questions are difficult, a lot of it is
3 not rocket science. Come up with the risks. Put the
4 controls in place. Test against them. Have good
5 governance in place.

6 I would say to everybody, we need to have a
7 discussion about harm. I think that's central to how we
8 move on from here. To the FTC and perhaps all regulators
9 that play in this space, these workshops are great. It's
10 been mentioned that we need to bring in some more
11 economists and data ethicists and scientists and so on.
12 So, everything just moved so quickly. It's like we
13 should schedule the next big data workshop a year from
14 now, schedule it now and get it done.

15 Maybe we should be having like an information
16 week where, you know, we're talking about best practices
17 and privacy one day, security the next, you know, data
18 governance in general, a piece about educating about, you
19 know, the FTC and everybody else about the technology and
20 the business models. It's kind of like shark week. If
21 you could combine them, consumers would tune in and there
22 would be the education piece right there.

23 MR. WOLF: Is that another dig at lawyers?

24 MR. SPADEA: No. My lawyers are my best
25 friends.

1 MR. WOLF: So, I'm hoping that just as privacy
2 by design is entered into the lexicon of all privacy
3 professionals, that data benefit analysis or benefit risk
4 analysis with respect to the use of big data will also
5 become something that's reflexive and something that
6 every privacy professional talks about.

7 I think that will avoid a problem I see with
8 Jeremy's analysis of focusing on who benefits. If you
9 put rigid one size fits all restrictions on the
10 collection and use of data, you're not going to have
11 benefits for anybody.

12 MR. OLSEN: Well, with that, I would invite the
13 audience to thank our panelists for a lively discussion.
14 Thank you, guys.

15 (Applause.)

16 MR. OLSEN: Jessica Rich, Director of the Bureau
17 of Consumer Protection, is going to give closing remarks.

18 MS. RICH: So, good afternoon. Many of you are
19 still here, I see. It's great. We've had a really great
20 day of discussion and debate regarding consumer
21 protection issues surrounding big data and, in
22 particular, its potential impact on certain consumer
23 groups.

24 My remarks will be short and sweet. They're
25 never quite as short as I think, but they'll be short and

1 sweet because I know it's been a long day for everybody.

2 First, I want to thank the team, many of whom
3 are sitting over there, that put together this terrific
4 event: Tiffany George, Katherine Armstrong, and Chris
5 Olsen here from the Division of Privacy and Identity
6 Protection; Katie Worthman, Patrick Eagan-Van Meter, and
7 Malini Mithal from our Division of Financial Practices;
8 and Jessica Skretch and Lesley Fair from our Division of
9 Consumer and Business Education.

10 And also thanks to our event planning and web
11 teams, our press office and honors paralegals for all of
12 their help. It takes a lot of people to put these on.
13 And thanks, of course, to our great panelists and our
14 audience and all of the folks who we spoke to and met
15 with as we were planning this event.

16 So, this workshop was part of the FTC's ongoing
17 program to examine emerging or growing consumer
18 protection issues. It was an inevitable follow up to
19 what we learned at our seminars on big data last spring,
20 what came out of our data broker report, and what we
21 learn every day by just opening up the paper -- yes, I
22 still get a paper delivered to my door, a hard copy --
23 and following industry developments.

24 Today we learned about many beneficial uses of
25 big data. For example, we heard case studies about how

1 big data can help fight discrimination, predict the risk
2 of homelessness, increase diversity in the workplace,
3 help ensure certain populations are getting the
4 healthcare they need, and actually empower traditionally
5 vulnerable populations.

6 But we also discussed the risk that big data can
7 lead to selective opportunities, stigmatization, and
8 discrimination. For example, Latanya Sweeney presented
9 some interesting preliminary questions about how big data
10 may impact the ads that visitors to certain web sites see
11 based on the presumed race of the visitor.

12 Solon Barocas discussed the ways in which
13 existing patterns of discrimination inherent biases
14 present in the use of little data, such as the
15 categorization of consumers based on their likelihood to
16 buy can be replicated with potentially greater scope or
17 scale in the use of bigger data.

18 Other panelists talked about how predictions
19 developed for one purpose, such as whether a person will
20 drop out of school or buy a particular product, could be
21 reused for more harmful purposes, or as a proxy for
22 income level, race, or other characteristics.

23 We discussed many important questions for which
24 we need to continue seeking answers. How will big data
25 be used for marketing, fraud detection, or the

1 eligibility for various offers? How do existing laws
2 apply to big data? Even apart from laws, how do
3 traditional approaches to privacy apply to big data? Are
4 transparency and choice still important and feasible in
5 this environment? What about data minimization and data
6 de-identification?

7 We also discussed what happens when certain
8 populations don't have the same sort of access to
9 technology as other consumers. Will inequalities result
10 from this lack of collection and use of data that could
11 otherwise provide benefits to these populations?

12 We began, but hardly finished, discussing the
13 overarching question that was the basis for this
14 workshop: how will all of these new and evolving
15 practices impact certain populations, and what steps can
16 and should businesses take to make sure particular groups
17 are not disproportionately or negatively affected?

18 I think it's fair to say everyone here today
19 agrees that big data is not going away and it's only
20 going to get bigger. Our collective challenge is to make
21 sure that technology continues to provide its many
22 benefits and opportunities to consumers while adhering to
23 core consumer protection values and principles.

24 To that end, our chairwoman this morning
25 outlined three steps for moving forward, which I'll

1 emphasize as my parting message. Actually, these three
2 steps, or themes, or whatever you want to call them, were
3 echoed down the line in this last panel.

4 First, as a law enforcement agency, the FTC will
5 work to identify areas where big data practices violate
6 the laws currently on the books that we enforce,
7 including the FTC Act, the Fair Credit Reporting Act, and
8 the Equal Credit Opportunity Act, and will bring
9 enforcement actions where appropriate.

10 Second, we will continue our efforts to examine
11 and raise awareness about the consumer protection and
12 concerns surrounding big data through speeches, consumer
13 and business education, which we certainly need to do
14 more of, and potentially follow-up events or a report on
15 this workshop.

16 And third, we will encourage businesses to
17 design their analytical systems with an eye to the
18 concerns that we've discussed here, avoiding bias or
19 disparate adverse impact on particular populations of
20 consumers.

21 Finally, I do want to mention that our comment
22 period will be open until October 15th. Please don't be
23 shy. Please comment if you have something to say. You
24 can file comments electronically or by paper. The
25 details are on our web site.

1 With that, let me just thank everyone for
2 coming. Have a great evening.

3 (Whereupon, the proceeding was concluded.)

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MATTER NUMBER: P145406
CASE TITLE: BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION
DATE: SEPTEMBER 15, 2014

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

DATED: SEPTEMBER 22, 2014

JENNIFER METCALF

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

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

ELIZABETH M. FARRELL