

FEDERAL TRADE COMMISSION

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FIRST ANNUAL

FEDERAL TRADE COMMISSION & NORTHWESTERN UNIVERSITY

MICROECONOMICS CONFERENCE

Thursday, November 6, 2008

9:00 a.m.

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P R O C E E D I N G S
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E C O N O M I C S
E A D V A N C I N G

MR. BAYE: Well, why don't we go ahead and get started. My name is Mike Baye. I'm the Director of the Bureau of Economics here at the Federal Trade Commission, and it's an absolute delight to be here to kick off the first annual FTC-Northwestern Microeconomics Conference. As you can see, we strategically put the firm "first annual" in the title as a commitment mechanism so that this will be ongoing even after I leave in a month and a half. Hopefully, that commitment mechanism will work.

Just a couple of announcements. I, first of all, want to, on behalf of the Federal Trade Commission, thank Northwestern University for their partnership in this ongoing endeavor, and in particular, to thank the Searle Center and Henry Butler for -- where is Henry? Is he here somewhere? There you are, Henry. Had breakfast with Henry this morning. Thank the Searle Center for their support in this ongoing relationship, and, also, the Center for the Study of Industrial Organization, in particular, Bill Rogerson, who was instrumental in helping forge this partnership with Northwestern University, along with Aviv Nevo and Scott

1 Dan O'Brien, Matt Weinberg, Rob Leitzler, Loren Smith,
2 Marissa Crawford, Mary Villaflor, Neal Reed, Matt Eaton,
3 Tammy John, and Alethea Fields, all played an important
4 role in making us comfortable and putting together a
5 great program.

6 And it's my distinct pleasure to be able to
7 introduce Bill Kovacic, our Chairman, who's going to be
8 kicking off this event for us. Chairman Kovacic is both
9 a gentleman and a scholar. He has served in various
10 capacities at the Federal Trade Commission. He's served
11 as a staff attorney; served as the General Counsel to
12 the Federal Trade Commission; he served as a
13 Commissioner; and most recently, he's serving as the
14 Chairman of the Federal Trade Commission.

15 And I know of no better person to kick off a
16 microeconomics conference than Chairman Kovacic. He has
17 a true love for research. He has a true love for
18 knowledge. And he's an academic in the very best sense
19 of the word. He's a distinguished attorney, as you all
20 know, but what you may not know is that he's co-authored
21 with a number of illustrious economists, including
22 Patrick Ray, Bob Marshall, and Leslie Marx. He hasn't
23 offered to co-author a paper with Mike Baye, but despite
24 that, I will introduce Bill, my friend and our Chairman.

25 CHAIRMAN KOVACIC: Thank you.

1 you looked at the budget of activities, that the element
2 of production or consumption that's involved in the
3 prosecution of cases could only take place sensibly if
4 we were making capital investments and making more of
5 them; making investments that in any one budget period
6 would have a long life, especially those associated with
7 building knowledge.

8 And I think there's been, over the past 15 years
9 or so, a very healthy norm or custom developed inside
10 the agency to increase awareness of that, and this
11 program is a manifestation of that awareness. Why do
12 this? First, I think it's necessary to our capacity to
13 deliver good programs, be they in the form of reports,
14 enforcement programs, and competition or consumer
15 protection, in advocacy before our legislature or state
16 bodies or, indeed, to have influence in a larger global
17 setting of shared authority; that without major
18 continuing, substantial investments in building
19 knowledge, that we won't be able to do good work in this
20 area.

21 The last element of that that I mentioned
22 becomes increasingly important. Regulatory authority in
23 the United States and around the world is highly
24 decentralized. We share authority for what we do in
25 both areas of our competence, competition and consumer

1 protection, with an astonishing collection of other
2 federal, state, and local institutions that have
3 concurrent authority, with no trumping mechanism that
4 dictates that any single institution controls the
5 decisions of the others. Internationally, it's simply
6 the same setting.

7 And in all of these areas, especially in a world
8 of over 100 competition authorities now, more consumer
9 protection authorities, you don't exercise influence by
10 compulsion. You exercise influence by persuasion. And

1 for what we do. And to some extent, we have drawn upon
2 that knowledge in a variety of ways, but I think by
3 achieving deeper integration with the research community
4 in North America, a two-way exchange of ideas, talking
5 more about what we do, drawing in more in real time what
6 researchers are doing, working through recruitment and
7 the attraction of the best graduate students into our
8 programs, we take a major step ahead in developing the
9 foundation for establishing true intellectual
10 leadership.

11 So, the program that Mike, Northwestern, and
12 their colleagues have set in motion today I see as being
13 an absolutely crucial, valuable part of an effort that I
14 think will have a very long life to build true
15 intellectual leadership and ensure that our programs, if
16 they falter, do not falter because of a lack of effort
17 to build a good base of knowledge. I look forward to
18 being able to sit in on some of the sessions today and
19 tomorrow, and I'm enormously grateful to the researchers
20 who have come to present their work here today.

21 And thank you, in particular, as Mike was saying
22 before, making the investment in the common pool of
23 knowledge that we'll all draw upon, but in your efforts
24 to assist us in doing what seldom happens in this city,
25 which is making long-term capital investments that will

1 serve the institution well over a long period of time,
2 resisting the impulse simply to make investments in
3 activities that yield immediate, appropriable returns;
4 in other words, to build a foundation that will last for
5 a very long time for the benefit not simply of this
6 institution, but the citizens and consumers we serve.

7 Thank you again, and thanks to Mike and to the
8 entire team.

9 (Applause.)

10 MR. BAYE: Thanks, Chairman.

11 Our introductory session will be held by one of
12 our partners, Scott Stern, who will be talking about the
13 market for ideas. So, Scott.

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MR. STERN: So, thank you very much for the opportunity to talk for a brief amount of time today, and I just want to kind of echo both the comments of Mike and Bill regarding this effort, and I think that sort of this is a very exciting beginning for a really interesting foundation.

I'm going to give a paper today that is a little -- I am going to be very up front. This paper is quite speculative, but I think very interesting, and I think potentially important for this audience and for

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1 also in many applications, often in contacts that are
2 far removed from the locus of invention. So, given the
3 uncertainty of innovation, you might come up with an
4 idea in context A, but what we know from studies of
5 innovation is very often the highest benefit is realized
6 by playing that in a very different context.

7 In particular, the value of that idea depends on
8 somehow matching it effectively with complementary
9 assets, and moreover, if somehow people who are
10 developing ideas that ultimately were applied and there
11 was the right price for that idea, that would provide
12 very effective signals for future investment in idea
13 production itself. So, that's sort of the very
14 principle, kind of high social return activity.

15 At the same time, markets for ideas are
16 actually, relative to almost every other transaction you
17 can think of, pretty darn rare. They are not absent,
 and in areas like I've studied in biotechnology, they

1 about markets for ideas, but what we really mean is I'm
2 some little entrepreneur, and I finally found someone to
3 buy my new idea, and I'm pretty much -- it's a bilateral
4 transaction, and very little of our analysis has really
5 distinguished between what it would mean to organize
6 knowledge, exchange, and diffusion as a market as
7 opposed to a series of isolated bilateral transactions.

8 Intriguingly -- and I'll come back to this, once
9 again, in the small amount of time -- the most robust
10 way we know how to do this -- and it was already alluded
11 to in both of the earlier comments -- is something that
12 we most -- essentially everyone here participates in:
13 The republic of science. Interesting point about that
14 market: The price of the ideas is exactly equal to
15 zero.

16 So, what we're going to do here -- this is, by
17 the way, joint work with Joshua Gans from Melbourne
18 Business School. We combine two distinct literatures.
19 On the one hand, this paper was motivated -- and I'll be
20 very explicit about that -- that I had the opportunity
21 to sit through a talk by Al Roth on sort of frontiers of
22 market design, and I heard that talk four times in the
23 course of a year, and I'm very slow, but by the fourth
24 time, I figured, huh, that's something that people who
25 think about innovation might think about, and I'll kind

1 of come back to that theme.

2 And I'm going to sort of take the ideas around
3 kind of economic analysis of the requirements and
4 challenges of market design, which is something that I
5 think a lot of you here will have been familiar with at
6 some level with our understanding of markets for
7 technology. And we are going to come up with kind of
8 three propositions that I'm, in the short amount of
9 time, not going to be able to kind of really develop
10 each of them in their full development.

11 But the first is that the very nature of what
12 ideas are undermines the market for ideas, and that's an
13 important point, that there's a kind of fundamental
14 source of the ability to allocate exchange in a market
15 with multiple players on both sides of the market.

16 The second is that the most robust market for
17 ideas are those where the ideas are free, and that's
18 going to raise this notion that Roth brings up of what's
19 called repugnance.

20 And then the third thing is that formal
21 intellectual property rights may not simply facilitate
22 isolated transactions, which is sort of how a lot of
23 work in economics, I think, is going to shape the agenda
24 there, but they actually play a crucial role in
25 overcoming challenges to establishing a market where

1 essentially the outside options for both buyers and
2 sellers is potentially other transactions in the market,

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1 endogenous outside options and raise new theoretical
2 challenges? And this is an example that Al Roth has
3 developed in some detail -- let me just -- has developed
4 in some detail.

5 What's the problem in kidney exchange? First,
6 the prices are zero, by law. If you need a new kidney
7 and somebody's willing to give it to you, you have a
8 very high chance that their blood type and other
9 characteristics are incompatible with your own body, and
10 in principle, then, and if there are two people who have

1 what happens is Michael and I will make an agreement
2 that your donor will give to me, my donor will give to
3 you, we do the operation at exactly the same time, and
4 we achieve very high returns.

5 So, Al Roth in the HAM lecture last year
6 developed sort of three criteria for effective market
7 allocation system, and I think if you haven't read this
8 article, it's actually quite effective, I think, in
9 synthesizing a lot of the work that's been done in
10 market design over the last ten years. One is, what do
11 markets need? They need thickness -- that's something I
12 think we knew probably already; we need lack of
13 congestion, essentially, individual transactions have to
14 be set up so they have enough time to look for an
15 alternative offer. Exploding offers are disasters from
16 the viewpoint of social efficiency. And finally, market
17 safety, which is a simple way of you have to be willing
18 to basically report your type, okay?

19 And finally, one thing that Roth and I think
20 other people have sort of kind of taken away is that an
21 important lesson for many real world market design
22 problems is that there seem to be important constraints
23 on these markets grounded in social behavior, the idea
24 that he talks about is repugnance, that social norms
25 play very significant informal and formal restrictions

1 on the ability to use prices to facilitate allocation.
2 The simplest point of this, on the one hand, when two
3 people get married at a price of zero, we all think
4 that's great, but the market for sex is mostly
5 prohibited. I haven't looked at the California -- San
6 Francisco proposition on that point, but nonetheless,
7 okay.

8 So -- okay, I don't have a lot of time. What
9 I'm going to do is the following. I've sort of
10 misallocated how much -- okay.

11 So, what I want to do is say, on the one hand,
12 what do we mean by a market for ideas? It's going to be
13 characterized by -- once again, by this distinguishing
14 feature between isolated transactions with may be very,
15 very high search costs, okay, but just isolated
16 transactions so that if you -- if failure in bargaining
17 occurs between the two members, if the idea is really
18 useful, the alternative option is seeking, for example,
19 an alternative buyer, versus -- excuse me, bilateral
20 transactions versus a market where the option is
21 endogenous.

22 And so there are going to be two features -- and
23 once again, we could go through more of these, but I
24 just want to highlight two -- there are two lots of
25 ideas which impact the challenge of market design in the

1 market for ideas. The first is something we call sort
2 of value rival, kind of coming up from -- kind of
3 thinking about ideas around nonrivalrous -- nonrivalry
4 of ideas.

5 So, in other words, in biotechnology, even if I
6 have a pretty strong piece of intellectual property, but
7 there's some tacit knowledge around it that I would have
8 to sort of disclose, one problem I face is that if I
9 approach a pharmaceutical company and start telling them
10 about my idea, not only, right, what I would really like
11 to do is approach actually many pharmaceutical companies
12 all at the same time, but the value of each of those
13 potential buyers from buying my patent is declining if
14 the general knowledge that's associated with that idea
15 is also being diffused through the bargaining process to
16 my -- to the buyer's potential competitors, right?

17 So, in other words, if I review -- right? So,
18 if I have a secret and I want to share it with Carl, and
19 Carl's competitor is Mike, right, is Michael, and if I
20 also say, listen, I have Michael is also willing to buy
21 the idea, Carl's like, well, now the secret's gone, and
22 so I don't even want to transact with you anyway. And
23 what that does is mean that the very fact that -- so,
24 the misappropriability problem actually degrades the
25 bargaining process.

1

A second problem, which we all know, any of

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1 marginal cost equals zero, and we're in Bertrand. That,
2 of course, inhibits my incentives to sell in the first
3 place.

4 So, you can sort of unravel the entire market if
5 the potential seller -- potentially buyers can also
6 become sellers and drive the price to zero. User
7 reproducibility in some sense results in a failure of
8 what Roth would call market safety. Individuals have
9 incentives to engage in strategic behavior that
10 undermines the welfare arising from allocation, and, you
11 know, you look at what happened in digital music in the
12 late nineties, and even today, that's what's happened,
13 right? All sorts of problems on the insider side,
14 because every single buyer can effectively become a
15 seller.

16 So, very quickly, we do know that there are some
17 people who think -- you know, initiatives that people
18 are taking to do that, from normal intellectual market
14 exchanges to something that people rel cos -2 TDeGo(TDTj5 rrD(17)Tj5

1 Chris Anderson in The Long Tale says, right, charges --
2 you know, essentially, in many cases, there's a -- the
3 psychology of free is powerful. The truth is zero is
4 one market, and any price is another. And it's true.
5 Micropayments are almost a complete failure. What you
6 see is people either have zero on their idea or they go
7 out, get a patent, engage in very big-time, you know,
8 kind of thinking about it, and sell out for a very big
9 price, but kind of the kind of intermediate range of
10 idea exchange is essentially missing. That's a missing
11 market in almost every context I can think of.

12 And the question is why? Is it something --
13 right? And what I just want to kind of in the -- and I
14 know I've gone over my time a tiny bit, but what I want
15 to do is just kind of raise up an idea that Roth first
16 introduces in the context of thinking about things like
17 kidney exchange, markets for throwing dwarfs, markets
18 for, you know, all sorts of things, is that there seems
19 to be a part of ideas where you can sell for free in
20 which people have -- in which there seems to be markets,
21 but the prices are free. And so just -- and it kind of
22 raises up this notion of what he calls a repugnant good.

23 So, let's try this. So, this I'll end on. So,
24 should the following -- just in your own mind, should
25 the following activities be permitted, in general? So,

1 Steve Jobs, we know, charges a price much greater than
2 marginal cost for the iPhone. I imagine most people
3 here are comfortable with that. How about a
4 pharmaceutical firm charging a price much greater than
5 marginal cost for a malaria treatment that was
6 completely discovered with public funds? Third, how
7 about the right of a record label to prohibit artists
8 from playing their own music with heavy penalties for
9 infringement?

10 How about licenses for university-developed,
11 sort of scientific-developed -- science-developed,
12 general-purpose research tools which involve very
13 significant -- where the form of the contract that's
14 agreed upon involves very significant restrictions on
15 the ability to publish follow-on scientific research?
16 There's a well-known case regarding the INCA mouse that
17 deals with that.

18 How about an auction between you and your health
19 insurance company to have exclusive access, either you
20 or the insurance company gets access to your genetic
21 profile? How about secret payments by the Government to
22 journalists or bloggers to express particular opinions
23 as their own? How about the sale of credit for a
24 discovery by a student to a faculty member?

25 All those are markets that somehow I imagine

1 that at least some of you might have some problems with
2 what's occurring at the bottom. And I would just
3 entertain that why we have problems with repugnance in
4 some markets and not others, all of which have to do
5 with the production and distribution of ideas, is an
6 interesting area going forward.

7 Thank you very much.

8 (Applause.)

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3 MR. BAJARI: Good morning, everybody. I'm Pat
4 Bajari from the University of Minnesota.

5 UNKNOWN SPEAKER: Is your microphone on, Pat?

6 MR. BAJARI: Can you hear me now? Okay, great.

7 Pat Bajari from the University of Minnesota, and
8 we're going to have next a short panel discussion on
9 merger simulations, and I want to just first briefly
10 introduce our three participants. The first, to my
11 left, is Mike Vita, who's an Assistant Director for
12 Antitrust at the U.S. Federal Trade Commission in the
13 Bureau of Economics. Mike has published numerous
14 academic papers within industrial organization and
15 antitrust. In particular, he's supervised a number of
16 merger investigations in which merger simulations have
17 been used. These include pet foods, ice cream, spices
18 and hospitals.

19 Next to Mike is Aviv Nevo, who's a Professor of
20 Economics and Marketing at Northwestern University.
21 Aviv has published widely on differentiated product
22 demand estimation and on merger simulations, and he's on
23 the editorial boards of a number of leading journals.
24 In addition, he's worked on several real world merger
25 simulations as an expert.

1 And finally, Gail Slater is a staff attorney at
2 the Federal Trade Commission. She's been at the Federal
3 Trade Commission since 2004, and she's worked on a
4 number of merger and nonmerger cases, most recently the
5 Whole Foods case.

6 So, what we're going to do is I'm going to give
7 everybody five minutes to make a brief statement on some
8 of their views about merger simulations, give them a
9 little chance to respond to each other, and then I'm
10 hoping you, the members of the audience -- I know
11 there's some people with opinions about merger
12 simulations here -- would be helpful and chip in by
13 asking some questions of our panelists. I think this
14 will be a fun topic to discuss where people have some
15 different opinions. So, please be thinking about this
16 in the background and help us out by participating,
17 because I'm sure your questions will be a lot better
18 than mine.

19 MR. VITA: I'm going to do a little PowerPoint.

20 MR. BAJARI: Okay, great.

21 MR. VITA: Okay. Let me start off with the
22 obligatory disclaimer that everybody here at the FTC has
23 to give. These are my views and not those of the FTC or
24 any Commissioner, and that's almost always true any time
25 I speak.

1 So, yeah, as Pat said, you know, I'm a manager
2 here in the Bureau of Economics. My job is to manage
3 antitrust investigations from the Bureau of Economics'
4 perspective. Merger simulation has been a big part of
5 what we do here in the Bureau of Economics for about the
6 last ten years or so, when some of these technologies,
7 if you want to call them that, first appeared on the
8 scene.

9 Back when those first papers were being written
10 back in the late nineties by people like Greg Werden,
11 Luke Froeb, at the Department of Justice and the FTC,
12 respectively, and Jerry Hausman and others, I think
13 people had a great deal of optimism about how much this
14 could add to our analysis of mergers, at least certain
15 kinds of mergers, and, in fact, Greg and Luke have a
16 paper -- a couple papers entitled, "Merger Simulation as
17 an Alternative to Structural Merger Policy," and by
18 "structural merger policy," I think they mean sort of
19 the traditional antitrust analysis where -- whereby
20 it's, you know, centered on document reading,
21 interviews, depositions, that sort of thing, calculation
22 of market shares, and everything that's in the 1992
23 Merger Guidelines.

24 Now, the typical simulation exercise, you know,
25 people who work at the agencies, you know, know what I'm

1 talking about, but for those of you who aren't real
2 familiar with it, what I mean, and I think what most of
3 us mean when we talk about merger simulation, is, you
4 know, assuming a particular functional form for demands
5 for the products in question, assuming a particular form
6 of competition, usually Bertrand competition, and
7 estimating the parameters of those demand functions and
8 then, combining that with the assumption about the
9 nature of market competition, predicting what the price
10 would be, and the output would be in the post-merger
11 equilibrium.

12 So, this has been going on for a long time. As
13 Pat said, I've done a lot of cases, you know, in

1 as well as from Commissioners is, how well does this
2 technology work? Does it do a serviceable job of
3 predicting what post-merger prices and outputs would be
4 like? And only now are we really getting to a point
5 where people are starting to address that question and
6 can say something interesting and important about that.
7 And the evidence on that question is fragmentary, but
8 there are a couple of papers -- one has been published,
9 one I think probably will be published in the next
10 year -- that get to that issue, and frankly, I think
11 the -- you know, the results of that research so far,
12 it's a little disquieting to those of us who have been
13 using this method and have been recommending its use.

14 The first paper is by -- was published by Craig
15 Peters of the Department of Justice, who went back and
16 looked at a number of consummated airline mergers and
17 went ahead and -- what he did is he took data from the
18 premerger world and went through the simulation
19 exercise, estimated demand functions, and then simulated
20 the post-merger environment, and he did it under -- you
21 know, the details of exactly what he did aren't terribly
22 important, with the possible exception of he assumed a
23 static Bertrand codec, which I'll get back to real
24 quickly when we talk about his results.

25 So, he estimated -- you know, he estimated the

1 demand functions, simulated the equilibrium in the
2 premerger and post-merger world, and predicted the
3 prices. Then he went ahead and compared the predicted
4 prices from that modeling exercise to the actual
5 changes, and he found -- and here's a table that I
6 reproduced from his paper -- there's -- frankly, you
7 know, it doesn't appear to have matched up all that way.

8 You can see the first line, the logit models,
9 the first -- the second column, where it's labeled
10 "Observed," those are the actual prices that, you know,
11 actually obtained from -- you know, from looking at
12 post-merger data. The logit and GEB, those are
13 simulated prices based on a couple different modeling
14 assumptions. And you can see, if you scan that, it's --
15 you know, it's some pretty big divergences between the
16 observed and the actual.

17 The second paper, the second piece of evidence
18 on this subject is being done here at the FTC by Matt
19 Weinberg and Don Hosken, and Matt's going to be
20 presenting tomorrow where he's going to talk about his
21 work in a lot more detail, so I'll just talk about it
22 real quickly. We looked at -- Matt and Dan looked at
23 two consummated mergers in consumer products. One is
24 motor oil, from the Pennzoil-Quaker State merger, and
25 the second one is maple syrup, from the Aurora-Log Cabin

1 transaction. Both these deals went ahead and were
2 consummated with no enforcement action.

3 Again, you know, in their paper, they used the
4 standard sort of thing. They estimate demand functions
5 under a couple different functional form assumptions and
6 go ahead and predict the post-merger price, then go
7 ahead and calculate or estimate the post-merger price
8 using private label products as the control. And what
9 they find in the results is that, you know, again, they
10 get a couple -- a couple of the predictions seem to be,
11 you know, pretty close to what actually happened, but
12 more generally, and the bigger problem is, the actual
13 price change for oil seemed to be pretty large and
14 pretty small for syrup. The simulated price changes got
15 those things exactly reversed. So, I mean, that's --
16 again, I -- that's somewhat troubling. You would hope
17 that any -- you know, you don't -- any serviceable
18 prediction tool would at least get the rank ordering
19 right.

20 I'll just -- I will go through this real
21 quickly. I mean, Peters in his paper does -- goes
22 through -- you know, tries to figure out exactly why,
23 you know, the observed prices didn't match up all that
24 well with the predicted price changes, and he does a
25 really nice exposition of that. I'll just skip through

1 that.

2 His conclusion is that in large part, though,
3 the inaccurate prediction may reflect the fact that the
4 premerger firm conduct wasn't Bertrand, which is our
5 conventional assumption in these kinds of exercises, and
6 there may have been something like tacit coordination
7 going on. Matt Weinberg and Dan Hosken, in their work,
8 they don't think it's -- you know, one of the
9 possibilities is cost or demand might have changed. In
10 their paper, they don't find evidence for that, and I'm
11 not -- Matt can talk more tomorrow about what he thinks
12 was really going on.

13 So, the bottom line, I guess, you know, as we
14 continue with this -- you know, with this process is,
15 we'll continue to do merger simulations in the bureau of
16 of economics whenever we think it's, you know,
17 appropriate and possible and the data permit it, but,
18 you know, has it fulfilled the promise that it -- you
19 know, some of the innovators predicted ten years ago
20 where it could replace or substantially replace
21 conventional analysis? I don't think so. It's helpful,
22 it's a useful piece of information, but we're not really
23 to the point where I think we can tell people, yeah, you
24 can really rely on this as a fairly accurate predictor
25 of what's going to happen in a post-merger environment.

1 So, that's probably about my five minutes. So,
2 I'll take a seat.

3 MR. NEVO: Okay, so I guess I'm -- I'm on this
4 panel, I guess, supposedly to be the big defender of
5 merger simulation, and I might be or might not be. I'm
6 not sure. I mean, I haven't really made up my mind yet.
7 So, we'll see how it sort of evolves.

8 I guess my main point has to do with, you know,
9 what do we really think about merger simulation? I
10 actually noticed that we -- both when Pat introduced the
11 panel and, you know, when we were asked to sit on it, we
12 discussed about, you know, merger simulation, but when
13 you actually look at the program, it talks about demand
14 estimation and the -- something of mergers -- yeah,
15 demand estimation for merger cases, and I think that
16 sort of reflects a little bit sort of differing views,
17 sort of -- for me, merger simulation is the idea that
18 you're trying to predict what the effect of the merger
19 will be, and I may be kind of just taking too much of a
20 dictionary sort of -- you know, trying to interpret what
21 the words say.

22 So, for me, you know, if you're doing kind of a
23 so-called structural analysis, you know, basically
24 Hirfendahl's and stuff like that, that's a merger
25 simulation. You're saying if a merger falls in a

1 particular range, you know, for Hirfendahl's, whatever
2 your cut-offs are, then the likely effects are going to
3 be high or the likely damage to consumers are going to
4 be high. If you are doing sort of a so-called
5 Staples-type analysis, okay, kind of -- as it's been
6 called, you're trying to predict what the effects of the
7 merger will be.

8 Now, then there's the narrow definition of the
9 merger simulation, which is, you know, the one that was
10 in the title and the one that I think Mike has already
11 referred to, which is this, you know, specific -- you
12 estimate demand, you take a Bertrand sort of assumption,
13 and you use that to sort of predict what the effect
14 would be. So, this latter one, I'm not going to be here
15 to sort of stand and defend.

16 I can tell you what my thoughts about it are,
17 but I'm not going to be defending that. I think the
18 broader view is sort of to understand that, you know, we
19 do need some sort of a model to predict what the effect
20 of the merger will be. We're trying to predict
21 something that we don't see in the world, and I think
22 the key is to bring sort of the best economics we can to
23 the problem, and sometimes, it might be estimating
24 demand and putting a Bertrand assumption, and in some
25 cases, a Bertrand assumption would be terrible. And I

1 think, you know, we have to sort of focus a little bit
2 at kind of understanding when, you know, these
3 assumptions will be good and when will they be bad. So,
4 that's just sort of in terms of kind of as a grand
5 overview.

6 Let me just say a little bit something about
7 retrospective study. So, obviously these need to be
8 done. I mean, they are kind of long overdue, and we
9 have to look at them. There's a bit of a problem to
10 looking at the evidence for particular -- particular
11 reasons. One is we forget, again, in this sort of grand
12 view, that we're taking -- we're picking one particular
13 method, but we ask, okay, what's the alternative? So,
14 yes, you know, there was a table there that this type of
15 merger simulation doesn't work well. Well, what happens
16 if we went based on Hirfendahls? Would we do any
17 better?

18 Now, it's a much harder sort of -- it's a little
19 bit like, you know, trying to pick up an olive with chop
20 sticks, right? I mean, it's very slippery if you're
21 trying to get -- you know, trying to get an exact sort
22 of something to beat up on when you just have this broad
23 thing of, well, you know, if the cut-off is 1500, then
24 everything about it is sort of fine. We never actually
25 put sort of something, you know, an all prediction that

1 someone can test later, but it's not clear that, you
2 know, the sort of alternative would sort of do any
3 better. The same, I think, for Staples-type analysis.
4 You could say, well, okay, what is your prediction of
5 the likely effects? How would that -- you know, what
6 would that have sort of worked out to? Of course, maybe
7 we don't have enough evidence, but we have to remember
8 sort of in that context.

9 The other thing that I find in some of this
10 discussion is, you know, I don't -- it's nice to know
11 that we get the right effect or not. I can see why the
12 FTC would care about that. But as an academic, I
13 actually would like to see more and sort of see where do
14 we need to improve our models? I think there's been too
15 much focus on did we get the right demand. I actually
16 think we're doing okay there. I mean, are we getting
17 any particular cross price-elasticity right? Probably
18 not. Now, it might be that for a lot of mergers, that's
19 going to be sort of the key, that particular parameter,
20 but I think where we're missing is sort of another
21 dimension.

22 So, if you actually look at some of the -- I
23 mean, you kind of mentioned them briefly, that sometimes
24 we're not even getting kind of the relative increases
25 right, and usually if you think hard, that's actually

1 know, that might not help, but, you know, that's, I
2 think, something that we have to ask ourselves.

3 Okay, I'll stop here.

4 MR. VITA: Thank you.

5 MS. SLATER: Good morning, everyone. So, I'll
6 piggy-back Mike's disclaimer. I don't speak for the
7 Commission either, and I'd add another -- oh, I beg your
8 pardon. I'm a low talker, so I'll start again.

9 I was just saying I was going to piggy-back Mike
10 Vita's disclaimer that I don't speak for the Commission
11 either, and I'd add to his disclaimer another
12 disclaimer, I'm not a Ph.D. economist. I'm here as a
13 humble staff attorney in the Bureau of Competition. So,
14 my perspective, obviously, is a legal practitioner's
15 perspective, and I was asked to -- you know, to think
16 about how I see merger simulation in the legal process
17 that I work in day to day, and that process being
18 obviously the merger review process here at the FTC and
19 the occasions when we go to court.

20 So, as I see it, there are three channels in the
21 legal process. We have our investigations. The vast
22 majority of cases end in either a consent or a closed
23 decision. There are cases where we do go to court. We
24 have the PI process. And now, increasingly, it appears,
25 we will have Part III merger cases here at the FTC. So,

1 I would say that there's a different role for merger
2 simulation in each of those three channels.

3 So, the first channel I mentioned is the merger
4 PI. I have some recent painful experience with that
5 channel in the Whole Foods case. It -- I think it's
6 real important to remember your audience here. We're
7 dealing with a District Court judge. He or she is a
8 very busy person. They are not an antitrust specialist.
9 They're also going to be subject to severe timing
10 constraints. They have a docket outside of the case
11 that they're working on with you. A lot of it's going
12 to be criminal. They have deadlines within that docket.
13 And, you know, as we learned last summer, they are
14 people who just may want to go to the beach the third
15 week in August, and that's going to dictate their
16 timing.

17 Additionally, they are going to be external
18 constraints timingwise. One of the first things that
19 the merging parties are going to say to them when they
20 first meet them is, you know, our financing is going to
21 fall apart in three weeks unless you, Judge, make a
22 quick decision on this case. So, and that's a pretty
23 uniform occurrence.

24 The other thing, final thing, to remember about
25 the District Court judges is that they -- they're going

1 to be risk-averse, and they're going to slavishly follow
2 Supreme Court precedent, and the precedent that they are
3 currently bound by, among them is Brown Shoe, and I'll
4 just, you know, I'll just quote what they have to follow
5 there, which is, you know, the proper definition of the
6 market is a necessary predicate to an examination of the
7 competition that may be affected by the horizontal
8 aspects of the merger.

9 So, if we're looking at merger simulation as an
10 alternative to structural analysis and the market
11 definition analysis, then that's going to be an issue
12 for pretty much all District Court judges, and it will
13 cut against that analysis. So, that's the merger PI.
14 Sorry to be so oblique, but I would also support what
15 I'm saying with a quote from Judge Hogan, who's here in
16 the District of Columbia, and some of you will be
17 familiar with his name. He was the Judge who decided
18 two PI cases in favor of the FTC. The first was the
19 Swedish Match case, and the second was Staples in 1997,
20 and he's quoted in this wonderful book, which I highly
21 recommend to you. It's World War 3.0. It's actually
22 about the Microsoft case. It's done by a guy named Ken
23 Auletta, who writes in The New York Times, I believe.
24 I'm sure it's a name you're familiar with. So, when
25 interviewed about the Staples case, here's what Judge

1 Hogan had to say about his decision-making process in
2 that case.

3 Judge Hogan recalls, "We had a lot of economic
4 evidence in Staples. We had a lot of documentary
5 evidence, although in that case, the econometric
6 evidence that the Government had was not at all
7 convincing to me." Sorry, folks. "I think the internal
8 company documents were more convincing. That's why I
9 stopped the merger." And then he went on to add, "a
10 case with a judge or jury is won or lost on a handful of
11 a few key points. You want to identify them early,
12 marshal your evidence, protect them, attack the key
13 positions of your opponent, and not get bogged down in a
14 lot of detail, because fundamentally, at the end of the
15 day, this whole case is going to get boiled down to a
16 35-page brief. At the appellate level, it's all going
17 to come down to that." And we've seen that happen with
18 the Whole Foods case.

19 So, the second channel I mentioned is the merger
20 review process here at the FTC, where, you know, in a
21 lot of cases, a closed decision is made or a divestiture
22 is accepted, and as Mike's already explained, there are
23 quite a few cases in the past ten years where those
24 decisions have relied in good part on merger simulation
25 done, particularly where the products involved were

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1 comments. I think he raises a very fair point. You
2 know, we're talking about merger simulation. I mean,
3 sort of everything we do is a merger simulation. You
4 know, I've talked about it in a very narrow sense in the
5 way that we frequently use it here at the FTC, but I
6 think you raise a good point, a fair point.

7 You know, when you do merger simulation,
8 quantitative merger simulation, like we have been doing
9 it, you know, it produces a point estimate of a price
10 increase that allows you to go out and say, how well did
11 that point estimate actually reflect what happened?
12 Nobody ever writes a paper like Craig Peters' paper or
13 Matt Weinberg or Dan Hosken's paper saying, well, how
14 well does the traditional way of plugging market shares
15 into Hirfendahls, how well did that predict the price
16 increase? Because, frankly, it doesn't predict the
17 price increase. It says, is there going to be one or
18 not or, you know, maybe it might say is there going to
19 be a big one or not, but it doesn't say, like, it's
20 going to be 8.2 percent. So, it is a bit of an unfair
21 comparison.

22 But I think that, you know, the bigger, harder
23 question for people like me, for people like Gail, and
24 for our Commissioners and for judges, you know, to the
25 extent they entertain this evidence is not so much is

1 basically, I think, took half of my previous five
minutes to respond to t 4cfive

1 challenge or really seek a remedy, I guess? My sense is
2 in the courts, it has had very little effect, in large
3 part or -- because it's so opaque, and the experts come
4 in, and it's quite sensitive, right? The functional
5 form that you use and also to other things, judges, very
6 hard for them to sort out. So, has it really mattered
7 or not?

8 MR. VITA: I'll take it. I'll try to answer
9 that. Well, let's start with, you know, how does it
10 affect the decision-making within the Agency? I mean,
11 really, I'm not a decision-maker, so I'm not really the
12 person that can answer that. You know, we hope that it
13 influences people, but, you know, again, what weight do
14 our Commissioners place on it when the Bureau of
15 Economics forwards a recommendation memo that includes,
16 you know, a simulation exercise as part of the evidence
17 that we think is relevant?

18 I think some Commissioners -- you know, there's
19 variance, but I really don't know. I mean, I --
20 that's -- it's not a question I can answer. I think
21 there -- with certain people, it goes right over their
22 head, and they attach a weight of zero. They're like
23 Judge Hogan. I mean, Judge Hogan's comments that Gail
24 read are disquieting, because they don't really get to
25 the issue. You know, again, we're talking about merger

1 simulation in a very narrow sense of estimating
2 functions and, you know, doing some oligopoly
3 simulation.

4 The stuff that was done in Staples, that's about
5 as simple a quantitative piece of analysis as an
6 economist can construct for antitrust, and if that's too
7 hard for people, we've got to find another line of work,
8 because, you know, I don't know what our contribution
9 is, at least, you know, in doing quantitative analysis.
10 You know, when you get to something harder like, you
11 know, the kind of stuff Jerry Hausman does where, you
12 know, explicit assumption about a particular oligopoly
13 model and that sort of thing, my guess is -- I don't
14 know how often that's actually been presented in court.
15 I don't know that we, at the FTC, have ever presented
16 such an analysis in court. The Department of Justice
17 may have. My guess is, you know, my guess is the
18 typical judge is not unlike judge Hogan. That's my
19 guess.

20 MR. BAJARI: Any other comments?

21 MS. SLATER: Well, I think some judges or at
22 least one that I'm aware of has accepted critical loss
23 as a simple story and relied on it quite heavily.

24 MR. VITA: Let's not go there.

25 MS. SLATER: But this panel is not about

1 critical loss, so...

2 MR. NEVO: I just have actually sort of a
3 related -- I mean, it's almost a question. I mean,
4 we're envisioning sort of -- you know, here, there was
5 sort of a -- I guess a quota sort of saying there was no
6 effect, but what would have happened if one side comes
7 up with an analysis and the -- I mean, so we should not
8 be mistaken by sort of having kind of the equilibrium
9 phenomena of both sides coming out and cancelling each
10 other, versus if one side came with a very detailed
11 model --

12 MR. VITA: There is actually a data point on
13 that. It's Whole Foods. That's exactly what happened
14 in Whole Foods. The FTC, through its expert, Kevin
15 Murphy, presented a Staples-like analysis of the likely
16 effects of the transaction, you know, looking at how
17 entry and exit events affected prices in geographic
18 markets, and the witness for the other side didn't do
19 anything like that. I mean, you know, did different
20 stuff, but he didn't do that. And, you know, we know
21 what happened there, so --

22 MS. SLATER: I think that witness even went on
23 to describe Kevin Murphy's work as some of the most
24 sophisticated modeling he had ever seen in his entire
25 career.

1 Is the best way to go at that a structural model? Is
2 there other empirical evidence we could develop that
3 would help put those numbers in context? Does anybody
4 have any opinion?

5 MR. VITA: Well, I mean, you know, we don't want
6 to get into a session where we complain about what the
7 judge did or didn't get right in that case, but there, I
8 mean -- I mean, I've -- my view of that case is we had a
9 pretty simple, straightforward story, and it was one
10 where the -- you know, if you view sort of merger
11 simulation more broadly defined, there we did it, again,
12 with some sort of reduced form, Staples, that exercise
13 that Murphy carried out. It was, I thought, a great
14 complement to an abundance of traditional kinds of
15 antitrust evidence that we got from documents and
16 testimony and that sort of thing.

17 Where I -- where I think, you know, when you
18 read, you know, the decision in that case, I think -- I
19 think to me, it betrayed a fundamental lack of
20 understanding of sort of the basics, just the -- you
21 know, why is the diversion ratio or the cross-elasticity
22 of demand important, you know, in trying to forecast or
23 trying to predict what the competitive effect of a given
24 transaction is likely to look like? And that -- you
25 know, the solution to that is to, you know, have these

1 guys go take Economics 101, I mean, which judges
2 sometimes do. I mean, there are, like, law and
3 economics programs to try to instill in them sort of the
4 basics.

5 But, you know, so I mean it is -- it is a
6 little -- you know, it is a little depressing, because,
7 I mean, how are you -- you know, the idea that somehow
8 an elaborate, sophisticated merger simulation exercise
9 based upon sort of state-of-the-art techniques, the kind
10 of stuff that Aviv and Pat do, you know, what role is
11 that going to play? Well, when a judge doesn't even
12 understand the fact that, you know, a high diversion
13 ratio between the merging parties, other things equal,
14 means there's a pretty high likelihood that prices are
15 going to go up. If you can't grasp that, you know, I
16 don't -- you know, I don't know what to do. Do more
17 research or something, you know, but it's -- it's -- you
18 know, that's very depressing.

19 What do you think, Gail?

20 MS. SLATER: I can't add to that, Mike. Sorry.

21 MR. BAJARI: Aviv, do you have anything to say?

22 MR. NEVO: Not -- maybe not directly sort of on
23 the real policy thing, but, you know, I think
24 ultimately -- and, you know, that's kind of pushing a
25 little bit, you know, going back to the retrospective

1 studies, I mean, I think if we look -- take a broader
2 view of these studies, rather than to, you know, beat on
3 any particular method, right, ultimately what we can get
4 from those is some sort of a database that will give us,
5 you know, if you want some sort of a mapping between
6 diversion ratios and actual outcomes, right?

7 So, I mean, I think if you have a translation to
8 show to a judge, show him, look, in the past ten years,
9 here are sort of mergers we thought these were the
10 diversion ratios, and these were the outcomes. Now,
11 whether they match exactly some Nash Bertrand prediction
12 or not, they're not going to match exactly, but if you
13 kind of show that there is sort of a systematic
14 relationship there, you know, I think at that point, it
15 does become relevant, you know, the diversion ratio.

16 Now, if there isn't a systematic relationship,
17 then maybe diversion ratio isn't important. I mean,
18 then we have to figure out why, right? But if it really
19 is relevant, we should be able to see it in the past
20 data. And, you know, again, not focus on the exact
21 specifics on did we get Nash Bertrand or not Nash
22 Bertrand, but is there sort of a general mapping
23 between, you know, the estimated diversion ratios and
24 what happened? And I think that's the kind of evidence
25 that you want to sort of put forward, and once you can

1 know the answer to that. I mean, we don't know -- you
2 know, I know the European -- a lot of the European
3 antitrust agencies, formal surveys are actually a pretty
4 important part of the decision-making process. That's
5 something we haven't done here, and it might be
6 something we might want to think about. I don't know
7 that -- it would be interesting to note if the people
8 who do that kind of analysis and gather that kind of
9 evidence have ever done any kind of ex post evaluation
10 to figure out, how well does this work? So, that's a
11 good question, but I -- you know, I really can't say any
12 more about it, but I think it's an interesting idea.

13 MS. SLATER: So, if I understood your question
14 correctly, you said there were two sources, I think,
15 identified as the polling, and then there's the internal
16 company documents, and there was -- there was a poll
17 done in the Whole Foods case, not by us, by Whole Foods,
18 and that was -- that was successfully, effectively
19 Dauberted by the FTC, because there were flaws with the
20 survey instrument and with its execution, and so, you
21 know, there are issues here in this jurisdiction with
22 surveys and Daubert that don't exist in Europe, because
23 it's an administrative process over there, and so that
24 they're more problematic here.

25 With regard to the internal documents, to me --

1 is, again, to continue and bring out good economics to
2 try and address these types of very hard questions.

3 MS. SLATER: And I will add, as the lawyer in
4 the room, you know, you guys are really smart guys.
5 What you do is very valuable. There is a place for it.
6 Know your audience and cut the cloth to fit the
7 audience.

8 MR. BAJARI: All right. Well, I'd like to
9 thank all three of our panelists. This was a lot of
10 fun.

11 (Panel Session One concluded.)

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1 onset of online markets for ticket resale.

2 The other interesting trend that there is, at
3 least in the United States, is a trend of deregulation.
4 There are five states that last year basically repealed
5 their anti-scalping laws. So, the legislative trend is
6 towards making resale okay, whereas before, there were
7 many restrictions on it.

8 So, I said that this is a controversial
9 activity, but, of course, most economists think of
10 resale markets as good things, and it's tempting to
11 think of resale markets as being unambiguously good
12 things, because the transactions that are taking place
13 are voluntary transactions, they are reallocating goods
14 to high-value customers or consumers, which is exactly
 the kind of thing we want markets to do, and these two

1 wouldn't have, and it could also have the opposite
2 effect on other people. It might cause people to wait,
3 thinking, why buy now when I know there's an active
4 resale market and I can just wait and buy a ticket
5 closer to the event?

6 It also increases competition for tickets in the
7 primary market, and it might -- it might make it so that
8 more people -- there is more intense competition early
9 on, right when the tickets go on sale for an event, you
10 might get this sort of mass onset of buyers trying to
11 get tickets all at the same time, and in particular, it
12 might be costly to get yourself early in the queue if
13 people are trying to get those underpriced tickets, and
14 the costs incurred should probably be weighed against
15 the benefits of reallocation, okay? So, this is another
16 complexity.

17 And then, finally, if you endogenize the primary
18 market prices, the presence of a resale market might
19 change the way the prices get set in the first place,
20 okay?

21 So, the first of these pieces is the pie
22 increasing piece, and the rest are all about how the pie
23 gets shared, and we want to talk about all of them in
24 this paper. We want to, but we won't. In particular --
25 I mean, this is a lot to talk about. We're going to try

1 pretty hard to see what we can say about the first
2 point, because we think that's sort of the first order
3 interesting thing. The others we're going to have
4 something to say about, how the pie gets shared among
5 the various market participants, but numbers 7 and 8, in
6 particular, we're not going to have much to say about
7 yet, which is unfortunate, because 7 in particular, I
8 think, is a very interesting question, and we have some
9 ideas about what we can do to address that, but at least
10 in the current draft of the paper, there's pretty much
11 nothing we can say about that particular point.

12 So, what we are trying to do, then, in this
13 paper is, you know, talk about how much resale increases
14 aggregate welfare by this -- by reallocating tickets to
15 high-value customers. We want to say something about
16 how that pie is shared, who's winning, and who's losing.
17 We also want to be able to say things about what would
18 happen if we could change fundamental characteristics of
19 resale markets.

20 So, for example, if we could exogenously lower
21 the costs of transacting in resale markets, what's
22 that going to do to the payoff to sellers, consumers,
23 and brokers? And the reason this is an interesting
24 question is you can view the Internet as having done
25 exactly this, right, just lowering the costs of

1 transacting in resale markets.

2 And then, finally, we're going to be able to say
3 some things about how resale markets would look
4 different if primary market pricing patterns were to
5 change, and we're going to do this by estimating a
6 structural model using very detailed data on 103 rock
7 concerts from the summer of 2004.

8 I'll tell you about the data in a minute, but
9 let me just give you a preview of what the model is
10 going to look like. It's going to be a two-period
11 model. The buyers in the market will either be brokers
12 or consumers, and the distinct -- the technical
13 distinction between them will simply be that a broker in
14 our structural model is a buyer who has no utility from
15 actually attending the event, okay? So, they only buy
16 with the anticipation of reselling.

17 And a key part of the model and what makes it
18 interesting and also what makes it complicated is that
19 it's a rational expectations model. So, when buyers
20 make their first period decisions, they have
21 expectations about how things are going to play out in
22 the second period, and those periods -- those
23 expectations are going to be correct in the sense that
24 the decisions that they lead to deliver equilibrium
25 outcomes in the second period that turn out to be, on

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1 buyers in this market aren't perfect predictors of the
2 demand for a given concert, and the reason we wanted to
3 do that is that there's plenty of evidence in the data
4 that some of the speculators actually get burned. Even
5 the professional brokers often buy tickets that they end
6 up having to unload at below face value. So, it must be
7 the case that there's some uncertainty, ex ante, about
8 the strength of demand for a given event.

9 Okay, so like many empirical projects, this is
10 one in which a lot of effort went into obtaining the
11 data and then working on data to clean it up and get it
12 ready to analyze. I'm going to spare you the details of
13 that process and instead just show you a picture of the
14 data. We have data from Ticketmaster, which is the
15 primary market seller for these concerts, and we
16 simultaneously have data from StubHub and eBay, which
17 are the two leading online ticket resale sites. So,
18 we're seeing what gets sold in the primary market, and
19 we can see, in parallel, what's getting resold in the
20 secondary market. So, this is the picture of our data
21 for one of the 103 concerts in our data set, Kenny
22 Chesney at the Tacoma Dome in Washington, on June 17th
23 in 2004.

24 So, if you look at the horizontal -- everyone's
25 looking at a different screen, so I can't point at a

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1 which is not surprising. There's a big premium for the
2 very, very best seats. So, this is a concert where the
3 tickets were, in general, underpriced. You can just see
4 that from looking at this picture, but this is
5 especially true of the very best seats. The front row
6 was vastly underpriced, and that's typical of concerts
7 in our data set.

8 But you can also see that here and there, a
9 ticket gets sold below face value. It doesn't happen as
10 often for this concert, but across our entire data set,
11 you'll see that it happens more than you might have
12 guessed. And another interesting fact here is that
13 there's some clustering of resales at the upper end of
14 the quality spectrum within a pricing tier, okay? That
15 is, if you look at the sort of second pricing tier, the
16 best seats within that tier were underpriced, and so
17 there's -- you can see that brokers were gobbling those
 up and reselling them. So, that's a picture of our

1 me scoot down here -- about a quarter of tickets -- a
2 quarter to a third of tickets are actually resold below
3 face value. So, that's either speculators that are
4 getting burned or people who are unloading tickets that
5 they ended up not being able to use and having to unload
6 them below face value, but that's sort of an important
7 fact that I don't think we anticipated going into this
8 analysis.

9 The timing of transactions -- in the primary
10 market, almost all the sales occur right after the
11 tickets go on sale. I'm not going to explain this
12 picture, but we used this picture, if you look at that
13 paper, as a way of justifying looking at a two-period
14 model instead of a multiday model. The fact of the
15 matter is that there's some overlap between these
16 markets, and there are some interesting dynamics, as
17 you'll see in Andrew's paper, which comes up next, but
18 we're pretending that those dynamics are uninteresting
19 so we can have a simpler model to estimate.

20 Okay. So -- okay. Just quickly, an overview of
21 the model. So, in the primary market stage, we've got
22 brokers and consumers arriving in a random sequence, and
23 they all have expectations about the resale value of
24 each seat, and they make their decisions based on those
25 expectations, and there's heterogeneity in consumers'

1 willingness to pay for a ticket. Of course, that
2 heterogeneity, that makes it so that there are gains
3 from reallocation, right? They're arriving randomly,
4 and the low-value guys might get lucky and arrive early
5 and get a high-value seat, and that's what gives rise to
6 gains from reallocation in the resale market.

7 And in period two, the way we clear the resale
8 market is we take the allocation that obtained in the
9 first period, and then we have a sequence of auctions,
10 starting with the highest-quality seat, we have the
11 holder of that ticket holding a hypothetical auction and
12 then randomly we select from the pool of potential
13 buyers, and we conduct a second price auction, okay?
14 So, that random participation is a major source of
15 friction in our model, and we do that sequentially,
16 starting with the highest quality ticket and proceeding
17 on.

18 We assume that there's no option to return to
19 the primary market. So, we assume away the idea that
20 you might buy a ticket in the primary market, sell it on
21 the secondary market, and then go back and buy another
22 ticket in the resale market. So, there's no
23 buy-sell-buy behavior. There's some evidence that that
24 occurs occasionally in the data, but we're assuming it
25 away for simplicity. I point it out because I don't

1 think it's an entirely innocuous assumption. I think
2 some of our conclusions might change a little bit if we
3 could fix that, which we're trying to do.

4 Okay, I'm going to skip that slide.

5 Yeah, so, I'm going to -- that's okay, because
6 I'm going to go quickly through this. So, the -- the
7 preliminary estimates are boring. So, I'm not going to
8 talk about those, but one thing that's a little
9 interesting is that we're estimating very high
10 transaction costs for consumers, transaction costs on
11 the order of \$70, and that's the cost of going and
12 selling a ticket on eBay. Now, you might think that
13 that represents a number of things, and I know Mary and
14 Alan Kreuger have talked about there being endowment
15 effects, and in our analysis, an endowment effect, if it
16 exists, is just embodied in this transaction cost.
17 Nevertheless, it's worth thinking about is that
18 transaction cost implausibly high? We think it's not
19 implausibly high, but it's something to highlight.

20 So, now I'm just going to give you a -- there's
21 no way I can go through all these numbers, obviously,
22 but I just want to give you an idea of the kinds of
23 counterfactual analyses we're wanting to conduct once we
24 have estimates of our structural model. We can sort of
25 simulate what was going to happen in the base case,

1 under the current regime, and then compare it to what
2 happened, say, if we zeroed out transaction costs,
3 right? So, if we take the parameters for transaction
4 costs for consumers and brokers and we just set those
5 equal to zero, we can then simulate what these resale
6 markets would look like and what the outcomes would be
7 for all the various players.

8 So, for example, if we do that particular
9 comparison, the number of tickets sold in the primary
10 market is largely unaffected, but the fraction of
11 tickets that get resold in the secondary market goes up
12 dramatically, not surprisingly, and then if you sort of
13 go down here, if you look at the bottom line in that red
14 square, total surplus goes up substantially if we zero
15 out transaction costs. So, eliminating a friction in
16 the resale market increases the size of the pie. So,
17 that's sort of what you would expect to see.

18 Some other kinds of comparisons we can do, we
19 can compare zero transaction costs to a market in which
20 there's no resale at all. If we could shut down the
21 resale market altogether, how is that going to affect
22 total surplus and the share of surplus? There's another
23 thing that we can do, which is that -- something that I
24 haven't talked about at all is that the reason these
25 resale markets exist is that the primary market prices

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1 but given that Ticketmaster is now conducting a lot more
2 auctions, in principle, there's data out there to test
3 that directly, whether holding an auction leads to less
4 resale in the secondary market.

5 So, you know, this paper is still a work in
6 progress, but the conclusions we're drawing at this
7 point are that coarse pricing in the primary market is
8 really what's driving resale activity. It's not just
9 that tickets are underpriced in a general sense. It's
10 that these guys are only setting two or three or maybe
11 four prices for tickets in a 10,000-seat venue, right?
12 So, that's a very coarse pricing structure, and the
13 resale market is largely about undoing that.

14 And then, finally, resale markets are
15 redistributing surplus in some fairly subtle ways, but
16 the numbers we're coming up with at this point suggest
17 that the observed levels of resale activity aren't large
18 enough to make a big difference in overall welfare; that
19 is, marginal changes to the amount of resale activity
20 aren't going to have a big impact on total welfare, but
21 large reductions in transaction costs, like the
22 reductions that have been affected by the Internet, I
23 would argue, could generate substantial gains in total
24 welfare, could increase the pie substantially.

25 And then finally, an interesting point that I

1 data only come from eBay and Stubhub, which are clearly
2 not the only two players in the market.

3 Now, forget in 2004, but, you know, now a days
4 when we think about it, people sell their tickets on
5 Craig's List, brokers have their individual Web sites.
6 There are other Web sites, other than StubHub, like
7 TicketsNow and things like that, and also, some
8 people -- there is still the shady scalper at the door
9 selling the ticket, and people might be selling tickets
10 to their friends. So, there are all those transactions
11 that are not part of the data that Alan and Phillip use
12 in the market. And, you know, people might be concerned
13 about that fact.

14 Now, I'm going to -- you know, the bulk of my
15 input to this discussion is going to be to present some
16 preliminary results that Alan Kreuger and I came out
17 from -- that we're taking from a national representative
18 survey of concerts that we ran from August to October
19 2006, where what we did -- and this is still preliminary
20 work that, you know, we're hoping to finish soon -- what
21 we did is we surveyed concert-goers inside the venue at
22 different -- at concerts, at 30 different concerts, that
23 were randomly selected across a universe of concerts
24 during those three months, and we asked them, you know,
25 what seat did they have; where they bought their ticket,

1 you know, how did they get their ticket; how much they
2 paid for it; you know, some reasons why they might have
3 gone through the secondary market, if they did; you
4 know, and other questions like that. And using this
5 data, you know, we can now compare how the eBay and
6 StubHub data that Alan uses with our data.

7 So, their overall resale rate is 4 percent, and
8 our overall resale rate is 10 percent. Note that that
9 is good, because, Alan, correct me if I'm wrong, but in
10 your estimation, you're implying that -- I mean you have
11 a parameter there that says that your eBay and StubHub
12 account for 50 percent of the data. So, that's, you
13 know, roughly correct. In our estimate, the market
14 shares of eBay and StubHub are 31 percent of the total.

15 Now, also note that Alan's data is from 2004,
16 and our data is from 2006. So, there might be also
17 differences in there, which the market has evolved in
18 the two years, and we know this market changes very
19 fast.

20 The average ticket price in the primary market,
21 in Alan's data, is \$83; ours is 81. If you look at the
22 price for the seat that they mentioned that, you know,
23 they're sitting in, but the average price that they
24 reported paying is \$88. So, again, roughly the same
25 ballpark.

1 The average resale price is -- from this paper
2 is \$111; ours is 122. Again, a similar ballpark.
3 Average list price of the resold ticket is \$89; ours is
4 91. Again, this -- this lines up pretty well. And we
5 also find that if you compare the second item with the
6 fourth, the average ticket resold is a better ticket,
7 it's worth more than the -- you know, than other
8 tickets, tickets that were not resold. So, the best
9 seats are resold, we did find out in our data, and the
10 average markup is 39 percent, whereas in our study, we
11 found a 36 percent average markup. So, again, that
12 seems really well -- to be matching up really well.

13 Now, a point that Alan mentioned is part of the
14 results -- as part of the results, he finds that the
15 consumer's transaction costs are \$63 versus the broker's
16 cost of \$12, and it's true that this might seem like a
17 high number, and a partial explanation that he gives,
18 you know, circles back to us in the endowment effect,
19 and that is a point that we also find in this survey,
20 which is that the consumer's valuation of tickets
21 increase after purchasing them.

22 And what we did to try to test if that effect is
23 true is we asked people two questions -- well, we asked
24 two different questions. We had two types of surveys,
25 and so we randomly asked half of the people one question

1 and the other half another question. And the questions
2 were, would you have bought your ticket if it would have
3 cost you \$300? And the second question, if someone
4 offered you \$300 for your ticket, would you have sold
5 it? And only 11 percent of the people said that they
6 would have bought the ticket for \$300. Now, since some
7 of the answers on the paper were clearly, because I paid
8 \$500, and now I -- 47 percent of the people said that
9 they would have sold their tickets for \$300, and so we
10 can see here an example of this endowment effect.

11 And so in conclusion, because I have to stop, I
12 think it's a very rich model that combines various
13 insights from the paper and uses unique data from both
14 the primary and secondary markets, and as Alan
15 mentioned, an interesting way forward would be to think
16 about the pricing in the primary market and how that has
17 changed with the evolution of the Internet markets.

18 Thank you.

19 MR. STERN: Okay. What I thought we would do --
20 and, Chris, tell me if this is a bad way of
21 organizing -- is maybe do one or two questions after
22 each paper? Is that fair? Where's Chris? Okay? Okay.

23 So, Michael.

24 MR. BAYE: A quick question for Alan. I was
25 just wondering, in the overall welfare effects story

1 that you're telling about secondary markets making
2 consumers worse off, and I think the welfare effects
3 were pretty small in the counterfactual experiments you
4 did. Can you identify whether any of those welfare
5 effects are stemming from something you might think of,
6 like double marginalization?

7 Obviously, in the Kenny Chesney ticket example
8 where you're selling out anyway, there is not any
9 reduction in overall number of ticket sales, but in the
10 overall sample, are the welfare effects being driven by
11 the fact that the double markup leads to fewer tickets
12 being sold ultimately, or are they selling out?

13 MR. SORENSON: That's an interesting question.
14 I mean, certainly -- okay, first of all, the factual
15 response to your question is that, no, not all of the
16 events in our sample sell out. I think roughly
17 two-thirds do. It's in the summary statistics table.
18 Most of the concerts in our sample, by the way, are
19 fairly large concerts by big artists. It's not a random
20 sample.

21 So, for at least half, probably more like
22 two-thirds of the data, like you said, this isn't a
23 relevant issue, but I think for the ones where the --
24 where the primary market tickets don't sell out, it is
25 kind of an issue, right, because you're going to end up

1 the way they do, just because we're already tackling a
2 lot in this paper, but there are tons of really
3 interesting questions about why the primary market
4 sellers do what they do.

5 But along the lines of what you were saying, one
6 interesting point, I think, is that, you know, there's
7 this trend to deregulate. There's this trend to repeal
8 anti-scalping laws, and most economists would say that's
9 probably a good thing, right? These are markets that
10 are -- you know, they're voluntary exchanges. It's
11 probably increasing total surplus. So, why bar them?

12 But one way to think about the legal argument
13 for anti-scalping laws is that you're trying to protect
the right of the seller to choose who gets to come/Share.7 0 TD(1

1 want to apply similar rights to sellers of event
2 tickets. I don't know, but that's one way to think
3 about the problem.

4 MR. STERN: Okay, and our next is going to be
5 Matthew Sweeting, and let me get up here. Okay, I'll
6 let you figure out -- he's going to be presenting --
7 well...

8 MR. SWEETING: Okay, thank you. So, I'm going
9 to be talking about the research which looks at the
10 dynamics that happen in secondary markets for Major
11 League Baseball tickets. So, this is the part of the
12 paper which Alan decided to extract for his book. So,
13 basically I'm going to be doing two things: Firstly,
14 describing the dynamics of prices that we see, and
15 they're going to be very stark and striking; and then
16 secondly, to be testing kind of explanations for why
17 what we see happens is the equilibrium outcome.

18 Now, I'm going to be looking at Major League
19 Baseball tickets as an example of perishable goods,
20 right? So, a ticket to a game is perishable in the
21 sense that after the day the game is played, the ticket
22 is effectively worthless. Now, another characteristic
23 which affects some of the analysis is there's also a
24 characteristic of fixed-date consumption, right? And by
25 that what I mean is independent of when you actually buy

1 the ticket, you can only go and enjoy it on the day the
2 game is played.

3 Okay, so the theoretical models which in the end
4 I kind of use my work to kind of illustrate are partly
5 driven by what we see in the revenue management
6 literature for how people should price perishable goods.
7 So, the basic theoretical structure in these models is
8 as follows: So, think about there being a seller who
9 has a fixed number of units to sell before a certain
10 date. We're going to assume that there's no commitment,
11 so the seller can continuously vary the price in
12 response to the time left until the game and how many
13 units they have left.

14 There's a very simple demand structure. So,
15 consumers arrive randomly, and we're going to assume
16 that they can't -- in the simplest models, we assume
17 they can't delay purchasing. And we're going to assume
18 the demand parameters are constant over time.

19 So, what we see in these models is the optimal
20 price at any point which the seller wants to set is
21 going to reflect the probability that a sale today
22 causes the seller to forgo a sale in the future, because
23 they won't have a ticket left when other sellers arrive,
24 right? So, what this means is that the fewer units you
25 have left, the more likely a stock out is going to be in

1 the future, so you want to set a higher price.

2 On the other hand, when there's less time
3 remaining, there's less opportunities for other sellers
4 to show up, and, therefore, that's going to tend to
5 reduce the price at which you want to sell, okay?

6 So, a robust -- what's been described as a
7 robust prediction in this model is the expected price --
8 the price you expect to observe should be falling over
9 time. So, falling is the moment when the goods are
10 going to perish approaches.

11 So, there's been actually -- I mean, obviously,
12 revenue management models are widely used by firms to
13 decide how to price products, but there's been
14 relatively little work actually trying to test the
15 motivations identified in the literature for how you
16 should price are actually being used in practice. And
17 when people have looked at this, for example, in
18 airlines, you tend, for example, to reject the declining
19 price prediction.

20 In airlines, at least as a couple of pretty
21 obvious explanations for why that might be the case, so
22 you might think that towards the end, consumers with
23 more inelastic demands tend to turn up, say such as
24 business people, and that's going to tend to provide the
25 airline with an incentive to increase prices close to

1 the date of departure, on the other hand, there may also
2 be commitment incentive, which the simple models
3 abstract away from.

4 So, a commitment model, you may -- a firm would
5 be thinking, well, if I tend to cut prices over time,
6 that's going to cause consumers to wait in the future,
7 and maybe to prevent future waiting, because I'm going
8 to win throughout with these consumers repeatedly, I
9 want to, say, commit to having a flat price schedule and
10 maybe an increasing price schedule.

11 Okay, so I'm going to be looking at secondary
12 ticket markets for Major League Baseball tickets, right?
13 Now, these are going to be, I think, a nice example to
14 look for kind of the revenue motivation, the declining
15 price, for a couple of reasons.

16 So, firstly, sellers in these markets are very
17 small, and this is actually one aspect where my data is
18 going to differ a bit from Alan's data. So, in Alan's
19 data, it's for concerts. A lot of secondary market
20 sellers are actually fairly large brokers. In my data,
21 a lot of the secondary market sellers are going to be
22 very small, and what they are is a season ticket holder.
23 If you own a season ticket, you have the right to go to
24 81 games. Even really loyal supporters don't want to
25 actually go to all 81 games. So, they sell their couple

1 of tickets that they have for the games that they don't.

2 So, when you look at HHIs, for example, numbers
3 like ten out of 10,000 are very common, which is much
4 lower than we would see, say, in airline markets.

5 Now, another feature is that because these
6 sellers are small, they are frequently selling kind of
7 one unit, and by one unit, I mean, say, a pair of
8 tickets. So, one pair of substitute products or one
9 unit of substitute products. So, in this case, we don't
10 have the inventory incentive, and in a theoretical

1 Now, the next thing I do is describe various
2 theories for why sellers cut prices over time, right?
3 So, one theory is this kind of revenue management
4 explanation, and just to be clear, what I mean by that
5 is as the game approaches, your ability to sell tickets
6 in the future goes down, you become keen as a seller,
7 and therefore, you tend to cut prices.

8 Now, an alternative explanation is, let's say,
9 residual man is becoming more elastic over time, right?
10 So, maybe consumers who arrive near the end, they are
11 going to have different kinds of demands than consumers
12 who arrive early, and that would cause you to cut
13 prices. And a third alternative is actually kind of a
14 seller learning story, where because you don't have
15 demand, you want to start off with a high price, learn
16 about demand, and then cut prices sequentially.

17 So, what I do in the paper is I reject the
18 seller learning explanation by testing kind of reduced
19 form implications of a learn model, and then I use a
20 structural model -- estimated structural model of the
21 seller's pricing problem to distinguish between theories
22 one and two and send up supporting the revenue
23 management motivation.

24 Now, that analysis focused on what the seller --
25 on the seller's incentives, why the seller is cutting

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1 Similarly, people who are buying tickets for
2 which future availability is more likely to be
3 uncertain, they are also tending to purchase earlier.
4 So, the patterns we see today are kind of consistent
5 with the buyer side of these models, explanations as
6 well.

7 Okay, so I just want to talk about two different
8 things. Firstly, very briefly, provide some evidence on
9 the fact that prices do decline and then explain what I
10 do, separating the revenue management and residual
11 demand explanations.

12 Okay, so a basic kind of linear estimating
13 equation, where we are going to have price on the
14 left-hand side, sort of dummies reflecting how many days
15 there are to go until the game, list -- we have got
16 listing characteristics, selling characteristics, some
17 variables measuring kind of how the teams are doing.
18 So, if a team suddenly gets in play-off contention,
19 prices tend to increase. And then the sort of fixed
20 effects, and the fixed effects are very important,
21 because obviously you might be concerned that what's
22 happening is that prices are falling over time because
23 unobserved ticket quality is declining over time.

24 But, in fact, what I am going to have in my data
25 is huge number of observations allowing me to include

1 fixed effects, which I regard as being pretty
2 exhaustive. So, for example, you know, very precise,
3 you know, controlling for the actual row -- section and
4 row the thing is in, including fixed effects for that,
5 and then also looking kind of within seller -- within
6 tickets, so the same seller selling the same ticket,
7 what are they doing over time? And that's how I try and
8 control the quality.

9 Okay. So, what are we seeing happen to prices?
10 So, as I mentioned, I am going to be using data from
11 StubHub, which is going to consist of data on list
12 prices, and then eBay, where I have list prices for
13 fixed-price listings, for auction listings, and
14 buy-it-now listings, and also transaction prices. Here,
15 we see in, say, the 40 days before the game, transaction
16 prices on eBay falling by about 25 percent until the day
17 the game is played and list prices on StubHub falling by
18 around 30 percent, okay? And what you can see is the
19 effects are estimated very precisely.

20 Now, when you look -- you can also see similar
21 effects -- I should say larger effects when you look at
22 e-Bay list prices and eBay auction start prices, and
23 similarly, when you look within seller-ticket
24 combination, you actually see, once again, even larger
25 effects. So, for auction listings, you see the auction

1 start price falling by 100 percent over time, and for
2 list prices, you see declines of 60 or 70 percent kind
3 of within ticket-seller combination.

4 Okay, so now let's turn to the question of why
5 are sellers cutting prices? So, just to kind of fix
6 ideas in a particular model, suppose there were two
7 periods -- okay. So, suppose there were two periods,
8 each period the seller has to set a price, unless,
9 suppose, if after the second period the ticket is left
10 unsold, he goes to value V , right? And that could be he
11 actually goes to the game himself or he gives it away to
12 a friend, for example. So, if you just set up the
13 pricing problem, in the second period, the marginal --
14 what I'll call the opportunity cost of selling is equal
15 to V . If you sell the ticket in the second period, the
16 amount -- you're getting the revenue, but what you're
17 forgoing is V .

18 In the first period, what you're forgoing is a
19 complex combination of V and the revenue you would have
20 got in the second period, right? So, what it's very
21 easy to show is that if the demand function, this
22 probability of sell function, Q , is the same in each
23 period, prices will fall -- your prices should fall over
24 time. On the other hand, there's -- and I'm going to
25 call that the revenue management explanation.

1 On the other hand, there's -- prices could also
2 be declining even if sellers are pricing in a very kind
3 of myopic way, because the Q function is changing. So,
4 if the Q function is becoming more elastic over time,
5 that would also cause sellers to cut prices.

6 Okay, so, what am I going to do empirically?
7 Well, at each point in time when the seller is listing
8 his ticket, what he's doing is he's setting the price to
9 maximize his revenues, recognizing that his cost of
10 selling is this opportunity cost. The opportunity cost
11 is not just V, but also reflects his future selling
12 opportunities.

13 So, what I do is I estimate, in the case of
14 fixed-price listings, a parameterized probability of
15 sale function, allowing that slope of that and the
16 intercept of that to vary over time, and then also I
17 control it for, for example, the competition effects.
18 I'm going to instrument the unobserved ticket quality
19 using some instruments which seem to work reasonably
20 well in this setting.

21 And then what am I going to do? I'm going --
22 from these estimates, I'm going to back out what's
23 happening to the opportunity costs of sale over time,
24 and then I'm going to perform counterfactual experiments
25 which say, okay, let's suppose we take these opportunity

1 the part of the seller, but we're going to assume he's
2 maximizing against the same demand curve in each period,
3 and because competition also tends to increase over
4 time, because there's more listings towards the end, we
5 are also going to assume he faces the same competition
6 as the game approaches.

7 What we see is we actually get price declines
8 sort of very similar to those we actually see in the
9 data, and that's true of both the models, and we see
10 similar effects when we look at auction list --
11 different kinds of auction listings as well. So, what
12 this tells us is the price-cutting patterns that we see
13 are driven by the declining of opportunity costs and not
14 by the changing elasticity of demand.

15 Okay, so I'll just wrap up, so -- allow more
16 time for discussion. So, what I provide is very robust
17 evidence for this tendency for prices to fall over time
18 that hasn't really been established before in the
19 literature in a perishable goods market. I then show,
20 you know, in a number of different ways why -- a number
21 of different kinds of pricing mechanisms, why sellers
22 are cutting prices over time, and it's because of the
23 motivation identified in the revenue management
24 literature.

25 I then look at what's going on with early buying

1 ticket resale. In fact, there was an article today
2 where Michael Wilbon had initially talked himself to

1 one reason would be if there was some market power that
2 accrued if you were able to get the lion's share of the
3 good in question. So, if you're selling off take-off
4 and landing slots, for example, or if you had increased
5 your returns to scale. In that case, winning the
6 early -- winning the early units gave you a leg-up. You
7 had a greater value of the later units than you did
8 those who didn't have any units yet. So, that was one
9 source of declining prices in auctions.

10 Another one, which is actually related, and it
11 was actually cited, occurs when you have horizontally
12 differentiated products being sold, because then, you
13 may have a preferred product -- we could be talking
14 about selling condominiums or we could be talking about
15 selling baseball tickets -- you've got a preferred
16 ticket, and simply buying earlier gives you the
17 opportunity to choose which of the preferred -- which of
18 the objects you get. All right.

19 Now, of course, we also saw rising prices, and
20 so when we talked about airline pricing, naturally
21 enough, people differed in terms of cost of locking in.
22 That's something that Andrew talked about. So, those
23 who had a lower cost of locking in would buy a ticket
24 early for the -- for an airline, and, in fact, those
25 people would be shunted to the off-peak flights, and

1 those who showed up at the time of the flight would pay
2 a higher fee. Okay, so, some of those same issues show
3 up here.

4 All right. So, what do we find in the current
5 paper? Well, clearly it's just an option value. I
6 mean, you've got some value of going to the -- you could
7 go to the game yourself, right? So, it's worth \$50 to
8 you to go to the game, but if you can sell it earlier
9 for 70, you'll do that, okay? So, there's just a
10 declining option value over time. As the clock keeps
11 ticking, your chances to sell to somebody else get fewer
12 and fewer, and that's why the prices are dropping. And
13 empirically, this turns out to be the best explanation.

14 So, obviously, Andrew mentioned declining assets
15 due to demand is another possibility or even learning by
16 sellers could be. Sellers might not know this demand
17 could be high for this game or this demand could be low,
18 and that might lead to screening over time, okay, but
19 that empirically is not what goes on here.

,r1srkb?o we fRyourself, right?7t7 -2 TD(,r1srk6D(fc

1 important here is that it's not the case that you
2 literally have no seats left. It's that you're looking
3 for a particular kind of seat, right?

4 So, some of us are going looking for seats right
5 behind the dugout and some of us are looking for seats
6 in the bleachers, and so it may, indeed, be that the
7 kind of ticket you're looking for may stock out even
8 though there are many, many other seats left in the
9 stadium, okay? So, that was the -- that was the
10 important point.

11 In fact, one thing I didn't catch, but you may
12 have had it in there, are there big differences across
13 teams in the price paths, because that might tell you
14 something. If, for example, the experience with Red Sox
15 tickets or Cubs tickets differs from the experience
16 with, say, Washington Nationals tickets. At least we
17 know for the Nationals, the prices are going to be a lot
18 lower.

19 UNKNOWN SPEAKER: They're very similar.

20 MR. GALE: Sorry?

21 UNKNOWN SPEAKER: They're very similar.

22 MR. GALE: They're very similar, okay. That's
23 interesting.

24 All right. And, of course, other reasons why
25 you are going to buy early, you know, search costs, and,

1 of course, the complementary investments, which is
2 something that shows up with attendance at a baseball
3 game or a football game, but it also shows up in a
4 newspaper a different form when we're talking about
5 airline tickets.

6 All right. So, one question I had, you know,
7 which tickets are available for resale? Is there any
8 kind of selection issue? Now, the paper is very, very
9 careful in controlling for -- controlling for quality,
10 but a natural question would have been, is it the case
11 that people decide to hold on to their tickets if it
12 looks like the game is going to be good, but they dump
13 their tickets if it looks like the game is going to be
14 bad? Now, of course, you've controlled for all sorts of
15 things, like how close the pennant race is, the
16 standings, and so on. So, I guess I can't say much more
17 than that, except you've obviously thought about that
18 issue.

19 Who does the selling? So, another question that
20 came to mind has to do with to what extent the teams are
21 involved. Now, your data come from, what, 2000-2007, is
22 that right? Teams have started to get a little more
23 involved in selling tickets themselves. So, the Chicago
24 Cubs now sell tickets through their Wrigley I premium --
25 it's called Wrigley I premium field service, whatever it

1 is. Ticket service? All right.

2 So, basically the Cubs sell through this
3 separate -- this separate arm, and, of course, the
4 question is, why would they do that? There are many
5 reasons why they might do that. One reason I've heard
6 is that there's revenue-sharing in Major League
7 Baseball, and if they can have their subsidiary making
8 profits from ticket resale rather than getting
9 themselves as primary sellers, that's to their
10 advantage.

11 All right. I should also note, by the way, this
12 past year, it's alleged that the Milwaukee Brewers sold
13 a huge chunk of their tickets, playoff tickets, through
14 a reseller, but the point is, that's only recent, and
15 given your time period, that's probably not much of a --
16 much of an issue. Okay. So, I guess I -- okay, so I
17 mentioned the Cubs and the Brewers.

18 All right. Forget about the first two points.
19 The issue about price changes. Now, you noted that with
20 StubHub, you're looking at listings, and if a listing
21 comes off, then that's interpreted as a sale -- not
22 necessarily, okay, because here's -- you've noted that
23 someone might list a ticket on StubHub and then might
24 change the price, and you're capturing -- you're
25 capturing that, and the first one is not deemed to be a

1 transaction, correct? Okay, good, because that would
2 have been another possible source of problem, and you've
3 caught that as well. All right, very good. Very good.

4 Okay, so just to finish up, one question is what
5 are the -- what are the applications? What have we
6 learned here? There are other industries obviously with
7 perishable goods, and note that hotels and airlines,
8 while they have one kind of pricing strategy themselves,
9 they're often selling through other entities now, right?
10 So, hotels are selling through consolidators. Airlines
11 are selling through PriceLine.

12 So, the price dynamics we see, if you call
13 American Airlines, may be very different from the
14 prices -- from the dynamics you see when we actually
15 look at PriceLine. And so, I'd be curious to see
16 whether you're getting the exact same dynamics you've
17 seen with baseball in PriceLine airline tickets, even
18 though the airlines themselves want to commit to high
19 prices for the people who just walk up to the gate.

20 And so I guess my time's up, so I'll just leave
21 it at that. Obviously, welfare would be another issue,
22 but again, let me say, it's a very, very nice paper.

23 MR. STERN: We have time for just a few
24 questions.

25 AUDIENCE MEMBER: (Off microphone.)

1 MR. STERN: We're behind. So, I'm managing my
2 interests versus keeping us on the time schedule.

3 Okay, and our last paper is by Steve Puller,
4 along with some number of co-authors. By the way, I did
5 remember, in fact, what the proposed title for this
6 session was when we were organizing it. It is, in fact,
7 you know, "That's the Ticket." So, here we go, more on
8 tickets.

9 MR. PULLER: So, I will continue on the theme of
10 talking about ticket pricing, in this case in the
11 airline industry, and actually, it's been brought up a
12 variety of times at least in the past paper what could
13 be going on in airline pricing. So, it's actually a
14 great setup to what we're going to be looking at. So,
15 this is joint work with my colleague, Steve Wiggins, who
16 is here, and Anirban Sengupta, who is at The Analysis
17 Group, and what we want to do is understand better
18 what's driving price dispersion in airlines.

19 So, we all know, at least through our own casual
20 empiricism, there's a fair amount of price dispersion.
21 So, if you flew to Washington yesterday, like I did, and
22 you had polled your fellow passengers, at least on my
23 flight you would find out that half of them had been in
24 Oregon knocking on doors in the past two weeks, but
25 you'd also find out that there's a fair amount of

1 of information which would be useful; in particular,
2 they strip it of ticket characteristics. So, we don't
3 know about refundability, and they strip it of
4 information that allows you to pinpoint what particular
5 flight that was. So, we can't assess load factor.

6 And so what we have is a unique data set which
7 we hope will allow us -- which has load factoring and
8 ticket characteristics, which hopefully will allow us to
9 assess these characteristics.

10 So, just to give you a preview of findings,
11 we're going to have some comparative static tests that
12 compare characteristics of flights on high versus low
13 load factor, and what we find is evidence that I think
14 Steve and I would characterize as modest support of

1 2004, and we're graphing this versus the number of days
2 in advance that the ticket was purchased, and each -- I
3 guess it's red dot here is the mean per that day of --
4 for that day in advance.

5 So, as you can see, not surprisingly, as you
6 wait until departure to purchase, in equilibrium, you're
7 going to be paying a higher price, but there's a fair
8 amount of dispersion around that, even as you come very
9 close to the departure date, and it's that dispersion
10 that we're seeking to explain.

11 So, let me describe briefly what the theoretical
12 models are that are giving us these comparative statics.
13 So, the first model by Jim Dana actually expands on
14 earlier work by Prescott and Eden, and he gives what I
15 think is a really intuitive example of stadium seating.
16 So, I'll just describe that intuition.

17 So, imagine there's a competitive -- there's a
18 stadium owner that is going to sell each of those seats
19 competitively. Prices are set in advance, which means
20 there's a ticket price that -- a ticket printed with a
21 price on it. There is no resale in this model. There
22 is two demand states that will occur with equal
23 probability. And consumers vary in their willingness to
24 pay. And consumers show up randomly and they take
25 whatever the cheapest ticket that's still available when

1 are going to sell with low probability. And what we'd
2 like to see is multiple realizations, so that -- because
3 our data are going to be transaction data.

4 So, in particular -- you know, so, for example,
5 here's a possible realization, where 60-something
6 percent of the tickets are sold. Sometimes, we're
7 actually going to see less sold and sometimes we're
8 going to see more sold. So, we're going to exploit that
9 comparative static. So, what we want to see is for
10 multiple realizations of flights with the same expected
11 load factor.

12 On flights that have higher realized demand, you
13 are going to have higher mean transacted fares, because
14 you're kind of climbing further up the fare schedule.
15 There's going to be more fare dispersion in transacted
16 fares. There's going to be a larger share of
17 high-priced tickets on the high load factor flights.
18 And if you have data on the sequencing of purchases,
19 you're going to find that for flights that are unusually
20 full, say seven days in advance, the tickets sold in the
21 last seven days are going to be higher priced. So,
22 we're going to take these comparative statics to our
23 data.

24 And the second model we're going to exploit is a
25 model by Gale and Holmes, slightly different setting.

1 It's a monopoly airline. There are two flights, a peak
2 flight and an off-peak flight. The consumers are going
3 to prefer one of those two flights, but they don't know
4 which one they prefer until right before departure time.
5 So, imagine there's some business meeting, you don't
6 exactly know when the meeting's going to occur until
7 right beforehand, and these consumers are heterogenous
8 in the sense that they vary in their time cost of
9 waiting.

10 So, what the paper shows is that airlines are
11 going to offer discounted advance purchase seats on the
12 off-peak flight, and essentially what this is doing is
13 diverting low time cost of waiting customers to the off
14 peak flight. And so the prediction we're going to take
15 to our data is to test if peak flights have fewer
16 discounted advance purchase fares, where we're going to
17 define advance purchase as those sales that were made
18 two to four weeks before departure, okay? So, those are
19 the two models within what we're calling scarcity
20 pricing.

21 A separate literature in yield management, we're
22 not going to directly test this, but just to make clear
23 how we see this as a different type of model, this is
24 basically playing off the fact that airlines might use
25 ticketing restrictions like refundability to segment

1 customers by their willingness to pay, and the key
2 feature of these models in terms of predictions is
3 different from the scarcity pricing models, is that the
4 yield management models don't necessarily yield sharp
5 predictions about the characteristics of tickets sold on
6 high load factor versus low load factor flights.

7 Okay, so the data we have, I've made references
8 a couple times, we have a census of transactions through
9 the fourth quarter of '04 through one of the computer
10 reservation systems that sells about a third of all
11 tickets through all of the major distribution channels.
12 So, for this, we have got more information than is in
13 data bank 1A, because we know for each itinerary the
14 various flights. We know which specific flight was
15 taken. We -- for each coupon in the itinerary. And we
16 know when it was purchased and what -- the days of the
17 flights. And we can combine this with some other
18 information to come up with a measure of what a given
19 flight's load factor is, measured with a little error.
20 And we're going to study 90 large routes for six large
21 carriers, essentially the biggest carriers, with the
22 exception of Southwest.

23 So, we also want information on ticket
24 characteristics or restrictions. So, we went to
25 another -- we went through another computer reservation

1 system. It turns out that there's a historical archive
2 so that one can look up what fares were. So, we're able
3 to match -- gather information from that second computer
4 reservation system on ticket characteristics.

5 The key one is refundability, where there's a
6 restriction on the days one could travel, and whether
7 there's minimum or maximum stay restriction, typically
8 like a minimum one-day stay restriction. So, we matched
9 that to our transaction data. We were able to match
10 about 36 percent of observations. We do some tests
11 which are in the papers where we're comparing
12 characteristics of the matched and unmatched, and in our
13 view, they're not that different. So, we think the
14 matched transactions are reasonably representative.

15 So, before I go into the formal test, let me
16 show you some motivating regressions that we view as
17 kind of descriptive analysis of the data, which are then
18 going to be consistent with some of our formal tests.
19 So, what we do in these regressions is we're just
20 regressing logged fares on ticket characteristics and
21 then on load factor.

22 So, in the first regression, we're only using
23 ticket characteristics. As you can see, as you buy
24 closer to departure date, you are going to be paying
25 more. A refundable ticket has about a 50 percent

1 premium. Travel and stay restrictions, so, for example,
2 a minimum stay restriction, corresponds to paying 8
3 percent less. And tickets where the traveler stays over
4 a Saturday night is a -- are transacted at a 13 percent
5 lower price. And from there, we're explaining about 70
6 percent of the variation.

7 Now we're going to add in load factor, both
8 actual load factor and expected load factor, and see
9 what the signs of those coefficients are. So, when we
10 add actual load factor, it is statistically significant
11 but economically fairly small, a standard deviation
12 increase in actual load factor means the ticket will
13 sell at 1.5 percent higher fare, and as you notice, the
14 amount of variation that we explain is not a lot higher.

15 We add in a measure of expected load factor, and
16 you also get that for flights expected to be more full,
17 that the fares are slightly higher. And you add both of
18 them in, and it seems that it's expected load factor
19 that is driving this.

20 So, from this we take, I guess, two things.
21 First, to the extent that load factor impacts fares and
22 equilibrium, it is economically rather modest; and
23 secondly, if you look at the coefficients of the ticket
24 characteristics after we add load factor, the
25 coefficients are fairly robust, which suggests that to

1 the extent that load factors is impacting fares, it does
2 so in a manner that's largely independent of the load
3 factor.

4 Okay. So, now to our formal test. So, the
5 first test is that for flights with the same expected
6 load factor -- if they have a higher realized load
7 factor, you are going to see higher price dispersion.
8 So, how do we measure this? So, what we do is we take a
9 given flight on a given day of the week. So, say
10 American flight 301 on Monday. We see that happen 12
11 times in our sample. We are going to take the average
12 of that as our expected load factor, and then we divide
13 all flights into quartiles.

14 Then, within each quartile of expected load
15 factor, we take the realized load factor, again divided
16 into quartiles. So, what the theory would predict is
17 that once I fill in these cells with some measure of
18 dispersion, that for a given column, a given expected
19 load factor, as you move up the column, fuller flights,
20 you're going to have a higher measure of dispersion.

21 So, the dispersion we're going to use is the
22 Gini coefficient. So, let me fill in those cells there.
23 So, as you look, as you move up any of those columns,
24 you're actually finding that, if anything, there's
25 actually a decrease in dispersion, although it's not

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1 Okay, so now to test these, I'm going to show
2 you a series of tables that look like this. So, let me
3 make sure I'm clear on -- clear to you guys on what
4 exactly these tables are. So, what we want to do is we
5 want to look at flights that are off peak and peak. So,
6 for an off-peak flight, we're going to take flights that
7 were expected to be low load factor and are load factor,
8 so no unusual shocks. Peak, expected high, realized to
9 be high. So, on these tables I show you, the left-hand
10 side is going to be our measure of the off -- allocation
11 for the off-peak flights. The right-hand side is going
12 to be the peak flights. And the boxes here are
13 basically percentages of all tickets sold for each of
14 these various carriers.

15 So, we're testing here, at least in the Dana
16 theory, is whether the fraction of seats sold on
17 off-peak flights that are low, discount tickets, group

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1 Now, let's directly test the Gale and Holmes
2 prediction about advance purchases. So, we're going to
3 define an advance purchase low-priced ticket, pulling
4 from the Gale and Holmes theory, as a group three ticket
5 that is sold two weeks or more before departure. So,
6 again, we're comparing left, off peak, to the right,
7 peak, and you can see the difference is, across the
8 airlines, there's zero percent difference, 3 percent
9 difference, 4 percent difference, for other carriers, 4,
10 2, and 4 percent. So, again, it is consistent with the
11 theory, but it doesn't seem that there's a large
12 fraction of tickets that's actually reallocated to
13 the -- low-priced tickets as reallocated to the off-peak
14 flights.

15 How much time do I have? Two minutes, okay.

16 So, let me go through our last test. So, the
17 last test, we want to ask the question, since we
18 observed -- we want to exploit the fact that we see the
2, a much t ,12

1 climbing up that fare schedule that I had drawn before.

2 So, let me leave the -- let me just kind of
3 focus on the bottom question here, in yellow. So,
4 essentially we're asking the question, for a ticket
5 bought seven days before departure, if the plane is 10
6 percent fuller than normal -- and the paper describes
7 exactly what normal is -- what percent more expensive is
8 the fare?

9 So, what we did here is we put everything
10 into -- we did a kernel regression for each of the
11 carriers and estimated this effect separately by
12 carrier. So, the steepest there is American, so that
13 would suggest 10 percent fuller in the last seven days.
14 The last seven days' tickets are priced 1.7 percent
15 higher. For the other carriers, it seems to be smaller
16 than that.

17 So, bringing all these tests together, we think
18 that -- we interpret these various tests as kind of
19 painting a similar picture, suggesting that, yes, in
20 fact, there is evidence consistent with the scarcity
21 pricing predictions, but it seems to be relatively
22 economically modest in terms of the quantity of seats
23 reallocated and what the pricing effects of that are.

24 It appears, in contrast, that there's much
25 stronger evidence that ticket prices -- so think back to

1 those motivating regressions -- that those ticket prices
2 are explaining more the variation. So, while it
3 certainly doesn't rule out models based on what we're
4 calling scarcity pricing, it certainly suggests that, at
5 least in future research, it would be very interesting
6 to look at how these ticket characteristics can be used
7 to segment customers.

8 Thanks.

9 MR. STERN: Great. And our final discussant is
10 Nancy Rose.

11 MS. ROSE: Okay. So, I wanted to say I found
12 this paper extremely interesting, and I'll have a few
13 comments of ways I think that the authors might push a
14 little bit more on their data, but I think this is a
15 fascinating insight into airline pricing that we really
16 haven't been able to get before because of the lack of
17 data that -- lack of information in the data sets we
18 traditionally use.

19 So, let me first -- first start with a little
20 bit of disclosure, which is I start from an extremely
21 strong prior, that it would be very difficult to explain
22 airline pricing without reference to at least some price
23 discrimination, that while I also think you've got to
24 refer to stochastic demand management, I think it's also
25 impossible to understand airline pricing without

1

So, the first line here is the one-way fare for

1 only the first in a series of papers from these
2 authors -- is that they've put together an amazing data
3 set that's got a third of all of the tickets sold in the
4 U.S. in the fourth quarter of 2004 with very detailed
5 information on those ticket characteristics, and I think
6 just the descriptive statistics are fascinating.

7 So, I looked at the Table 6 that Steve gave you
8 a little taste of, and, you know, just lots of
9 interesting patterns jump out there that have nothing to
10 do with either stochastic demand management or price
11 discrimination, or not immediately. For instance, the
12 large fraction of tickets that are sold in the last six
13 days before flight departure, which, you know, we really
14 didn't have aggregate data on that that would let us
15 look at that, and I imagine you could do a lot with
16 those tickets; or if you go -- flip through that at the
17 break, the very high fraction of group one -- remember,
18 those are the really high-priced, unrestricted
19 tickets -- that U.S. Air sells, unlike all the other
20 carriers.

21 My guess is -- and this might be something you
22 guys want to do -- if you pulled the shuttle routes out
23 of that, it might look a little different, but I thought
24 that was fascinating, and clearly, having a high
25 fraction of group one tickets isn't enough to make you a

1 highly successful, profitable airline. But anyway, the
2 descriptive stats suggest a lot of interesting data to
be mined yet in this project.

1 hundred. You couldn't tell anything about the
2 underlying demand for a given flight.

3 So, I might just say a little more thought about
4 that, is there a way to get a better indication of what
5 demand is? And my thought was it might at least be
6 interesting to look at the periods that are excluded
7 from this analysis, which is the -- so, this is the
8 fourth quarter, includes holiday travel. We know and
9 the airlines know that every flight that flies out on
10 the Tuesday or Wednesday before Thanksgiving is going to
11 be full.

12 Now, the kind of demanders are different, so you
13 might expect the price level to be different, but
14 there's no probability of -- at typical airline prices,
15 right, there's no probability of a seat going -- going
16 out unsold on the Wednesday before Thanksgiving, apart
17 from kind of price discrimination stories, maybe. That

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1 results, which is I suspect, given that all of these
2 routes are basically hub routes, the way that the routes
3 are selected are the very largest routes, those are
4 routes on which the hub carrier is likely to have
5 corporate discount deals with significant employers in
6 the area, and I'm guessing first that that explains why
7 some of the fares don't perfectly match the
8 restrictions, although you might be able to get within
9 the range.

10 But secondly, that some of those -- those
11 tickets that look like unrestricted, very low-priced
12 tickets sold right before departure may, in fact, be
13 corporate discount tickets that are -- I'm sorry, that
14 look like restricted tickets sold right before departure
15 are, in fact, unrestricted corporate discount tickets.
16 So, you know, I bought my ticket two days ago to fly on
17 the shuttle. I paid 230 because of a corporate discount
18 rate. The unrestricted walk-up fare is 448. My ticket
19 looks more like a discounted, advance purchase ticket,
20 but it doesn't have restrictions associated with it.
21 And you might be able to do something by looking at
22 nonhub carriers out of hubs.

23 And then finally, I'd like to push them a little
24 bit harder to say something more -- to take more
25 seriously the revenue management literature and what the

1 implications of stochastic peak load pricing also are
2 maybe for expected revenue per seat or expected revenue
3 per flight, and I'm wondering if you could do a little
4 something more with that, again, to get crisper
5 predictions that you could then test against the
6 patterns and the data.

7 But overall, let me just say, I found this a
8 fascinating paper, a great contribution to the
9 literature, and I look forward to not just the revisions
10 of this one, but the many papers that are to come.

11 Thanks.

12 MR. STERN: Okay. So, we have an incentive
13 conflict, because if you have -- we probably have time
14 for one or two questions, and then we have lunch, and so
15 are there one or two questions that we want to do
16 before?

17 And why don't --

18 AUDIENCE MEMBER: I have a question for all
19 three of you. It seems to me that all of you have made
20 assumption of exogenous entry of consumers. For Alan, I
21 think it's random participation in the secondary market;
22 for Andrew, it's also consumers arrive exogenously. I
23 think you also mentioned that consumers arrive
24 exogenously -- randomly. So, I'm wondering the impact
25 of this assumption on your work.

1 For example, in Alan's work, if consumers -- I
2 would imagine consumers who participate in the secondary
3 market would be -- will have higher value of time, and
4 I'm wondering maybe like you leave out very small
5 welfare impact of the resale market is partly determined
6 by that. And I think this assumption may have different
7 impacts on all three of your work. So, I just want to
8 know.

9 (Inaudible response.)

10 AUDIENCE MEMBER: So, what prevents you from
11 making alternative assumption?

12 AUDIENCE MEMBER: (Inaudible response.)

13 UNKNOWN SPEAKER: Could you go to the
14 microphone?

15 MR. PULLER: So, I think undoubtedly that the
16 types of customers that arrive right before departure
17 are different than the customers arriving maybe 30 days
18 before. We're kind of taking the theory seriously as to
19 what the predictions would be if it's purely scarcity
20 pricing, but I would completely agree with you that it
21 would be interesting to try and understand the
22 characteristics of the customers that are arriving early
23 versus late.

24 MR. SWEETING: (Off microphone.)

25 UNKNOWN SPEAKER: You can also look at time

1 slots, which we have done some preliminary work on time
2 slots. It's a way of getting the pure exogeneity of
3 load factor, so you look at time slots and use that as
4 an instrument, because the demand would be very
5 systematically different from, say, 7:00 to 10:00 a.m.
6 in the morning -- (off microphone).

7 MR. VITA: Any of you guys who are talking, you
8 have to talk into the microphone.

9 UNKNOWN SPEAKER: But I think we're done.

10 MR. VITA: Okay, we're done.

11 (Paper Session One concluded.)

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1 E E ADD'E B CA' A 'i

2 MR. SCHMIDT: Okay, it seems quiet enough that
3 we can go ahead and get started. I just wanted to
4 quickly say, I'm Dave Schmidt. I run our Office of
5 Applied Research here in the Bureau of Economics. And I
6 just wanted to send an invitation out to a lot of the
7 researchers here that we think there are a lot of great
8 complementarities between economics, doing research and
9 people here at the agency, specifically at the FTC.

10 And if you've got like good empirical models or
11 theoretical models that you're sort of looking for an
12 application for, I encourage you to come and grab one of
13 us and talk to us, because we have a lot of experience in
14 industries and we might be able to think of something
15 that fits well. I think there are great
16 complementarities there between us and I think our
17 lunchtime speaker here really embodies that.

18 He's recognized those complementarities
19 through, I guess, integration of some sort by serving at
20 the Department of Justice as the Deputy Assistant AG for
21 Antitrust, and currently as the Transamerica Professor of
22 Business Strategy at UC Berkeley. And we've all
23 benefitted from Carl's research and writings and, now,
24 today, from his lunchtime speech here on market
25 definition.

1 exercise, isn't giving as much pay-off anyhow.

2 And then we have the back -- what I'll call
3 back end where this presumption could be rebutted by the
4 parties through arguments about entry, repositioning,
5 efficiencies. Or not just rebutted by the parties, but
6 the agency itself, of course, could say, oh, we're not
7 going to bring a case, even though we've got high
8 concentration, because we think these other effects are
9 strong.

10 When you're using a consumer welfare standard,
11 there's a whole separate debate about whether that's the
12 right standard, but that seems well-established and we're
13 just totally accepting and embracing that in this
14 proposal.

15 So, the goal here is actually, in some ways, to
16 be rather modest, in some ways to be a bigger change in
17 slotting into this structure an alternative way to get a
18 presumption. Not to replace this method, but to offer a
19 second root for the government to get a presumption, and
20 then, continue on into the back end to see if we've
21 rebutted in the same fashion. So, that's the idea,
22 without using market definition.

23 Now, I'm really thinking of differentiated
24 product mergers, of which there are plenty. I mean, Mike
25 Vita and his whole shop, it sounds like they spend their

1 -- it's a lot of what they do, actually, at least the
2 ones you mentioned maybe in the context of merger
3 simulation. And, you know, many of you who work on
4 mergers will be -- you know, there's just a wide class of
5 mergers, okay?

6 Maybe my experience is a little -- not totally
7 representative because I haven't done steel mergers or
8 chemical mergers very much, but a lot of the mergers, I
9 think, would fit here, you know, that were differentiated
10 products. And I listed some of the industries here. I
11 didn't even mention, you know, retailing tends to fit in
12 here, too, or something like a hospital merger would be
13 similar where the differentiation may be geographical as
14 well.

15 So, a very large class, but we're not claiming
16 all mergers. So, it's unilateral effects and these
17 differentiated products.

18 We're going to focus on pricing competition in
19 the same way that the merger guidelines do in terms of
20 thinking about measuring things and effects, which, as we
21 understand, price is just one dimension of competition,
22 but it's a good sort of proxy for other dimensions, and
23 when we try to measure effects, we'll look at prices
24 first and then -- at least initially. There's some stuff
25 in the paper about how you would apply these same ideas

1 to innovation competition as well.

So, this class of mergers, as I said, is veryelnt B,y4p.0l

1 would be, it's very hard, because these predictions are
2 very hard. I mean, look, we have trouble retrospective,
3 figuring out what happened even after the fact. So, I'm
4 in the camp, certainly, and I know Joe agrees with me,
5 that some ability to get a presumption is important if
6 one is going to have effective merger control as a
7 practical matter. That's debatable, obviously, but
8 that's where we're coming from.

9 So, part of the motivation here, I guess a
10 large part of the motivation is that we, and I think many
11 other economists and lawyers, see a lot of difficulties,
12 problems, even dysfunction with the current system, this
13 current structure based on market definition and
14 concentration. I think the root of the problem is that
15 that structure was put in place -- and it dovetails much
16 better with coordinated effects cases than unilateral
17 effects cases.

18 If you think about a case where you say, gee,
19 these companies are merging, I'm concerned this is going
very significant to citizens

1 be in a cartel after this and there used to be six, I can
2 think about it that way. And that's what this
3 hypothetical monopolist test does. It tries to figure
4 out what that group of firms is that would profitably run
5 a cartel.

6 So, it's actually -- the market definition
7 actually is well-matched. I mean, it still has
8 difficulties of various sorts, but at least it's
9 logically matched with the coordinated effects theories.
10 And that's just not true for unilateral effects, okay?
11 It's just not, okay? Because unilateral effects is
12 really what's going on between these two firms given some
13 cloud of other firms around them and drawing a boundary
14 on which other set of firms we want to include or exclude
15 becomes somewhat artificial and is not the direct
16 question at hand.

17 And I make these assertions here. This method
18 can be misleading, uninformative, distracting. Those of
19 you who work in this area will, I think, mostly nod your
20 head and agree. Those of you who aren't convinced, you
21 will have to talk to me later or talk to other people who
22 work in this area and, perhaps, you'll then be convinced.

23 It's also the case that the method, as
24 described in the guidelines, introduces various, I say
25 here, arbitrary parameters. There's a bunch of things

1 that one has to do so you have the size of the snip. So,
2 it's 5 percent most of the time, but could be more or
3 less, the HHI's thresholds, 1,800, Delta, HHI of 100.
4 Thirty-five percent safe harbor. These are all numbers
5 that -- I don't mean totally arbitrary like they were
6 picked out at random, but, you know, where do they really
7 come from? You know, what's the basis for those and
8 what's the logic behind why it is 1,800 or a change in
9 the Herfindahl of 100 or 150?

10 Maybe you could go back to some study of cross-

1 exercise is reduced because what do we really make of it
2 when we say, okay, the Herfindahl goes up from 2,200 to
3 2,700. Then the judge will say, oh, that's interesting,
4 but does that tell me much? So, there you are. So,
5 that's not establishing a very strong presumption except,
6 I guess, in the case where it's very, very high
7 concentration.

8 So, we want to come up with an alternative
9 simple test diagnostic and the -- I want to draw a
10 parallel here between the existing concentration base
11 test and our test. UPP here stands for upward pricing
12 pressure that I'll be talking about quite a bit in the
13 slides to come.

14 So, if you think about, again, sort of the
15 Gestalt of the Herfindahls, there is an underlying robust
16 economic idea there, which is if you have a large share
17 of the market and you increase output or lower price, you
18 lose some revenues on all your inter-marginal units, as
19 you have larger share. You may pick up some business
20 from others. But as one firm becomes larger in the
21 market, they have less incentive to increase output or
22 lower price. It's just -- you can see that in the
23 Cournot Model most clearly where Herfindahl type numbers
24 can come up.

25 In my paper with Joe Farrell, actually, in the

1 AER and the other paper in the RAND Journal in '89 and
2 '90, we went through -- and other people have looked at
3 the relationship between Herfindahls and Cournot. But
4 there is an underlying robust idea relating share to
5 marginal revenue. It really works pretty well. I mean,
6 that idea really fits more with homogenous products and
7 output choices and not so well with differentiated
8 products.

9 So, what we're doing is saying, well, let's
10 look at -- think more at this level, the Gestalt level of
11 differentiated product and pricing, and we're going to
12 look to see whether the merger will create pressure for
13 prices to go up, a very robust idea that we will develop
14 in a specific model of Bertrand competition, but the idea
15 will be very robust, just as concentration-based ideas
16 are robust, although they're developed in a rather
17 specific model of Cournot. That's the parallel.

18 Now, let's develop that test. That next group
19 of slides does that. So, in a way what you might do is
20 draw a line here, take a fresh start. Put the guidelines
21 aside, as difficult as that might be for some of you.
22 Just imagine you're taking a clean sheet approach to
23 thinking about how you would evaluate a merger,
24 differentiate a product industry, what would you do? And
25 you'd say, I think two things. You'd say, well, gee,

1 these companies have been competing against each other,
2 also against others. But what the merger's going to do
3 is they're going to stop competing against each other.
4 That's what we mean by unilateral effects. And that will
5 generally encourage some higher prices. That's a pretty
6 general idea.

1 that right in. We're just going to go right there.
2 We're going to go right to that without any -- you know,
3 nobody's telling us some other artificial construct.
4 We're just going to do that directly, okay?

5 So, what does that mean? Well, the loss of
6 direct competition, we can -- I'd use the term
7 "cannibalization." Of course, what I mean by that is
8 before we merged, when I got business from you, that was
9 in addition to my product, after I acquire your product,
10 if I manage my product to get more sales from your
11 product, I'm now cannibalizing my own sales. So, that's
12 not nearly as big a win as it was before the merger.

13 So, how do we think about that? So, we've got
14 some notations. We've got two firms, let's say. The
15 very simplest structure you could think about this: Two
16 firms, profit levels. First, I'll do it abstractly and
17 then in the next slide I'll talk about prices. Just
18 think generally that I run product -- I'm Firm A.
19 There's some strategy beyond variable. If I do more on
20 that dimension, I sell more. X is output. But if I do
21 that, it cuts into your profits. This might be lowering
22 prices. It might be marketing more. It could be
23 improving my product. I don't care.

24 So, the merger internalizes this impact.
25 That's what I mean by cannibalization. So, what you can

1 figure out is, if I think about the -- if I think of the
2 cost of selling one more unit of my product, well, this
3 cannibalization is equivalent to a cost increase, I mean,
4 marginal cost increase there for my product. That's what
5 I call Tax A. And it's basically -- which is how much
6 your profits fall if I sell one more unit. That's
7 basically an opportunity cost term that gets internalized
8 through the merger.

9 And that's what that ratio is, how much your
10 profits fall by -- if I increase my -- if I act more
11 competitively, how much your profits fall per unit extra

1 So, we measure that and talked a lot about
2 that. Of course, that came up earlier this morning. So,
3 now, we figure, well, how do we then come up with this
4 opportunity cost term or tax? Well, if I sell one more
5 unit that comes at your expense, based on the diversion
6 ratio. And then how much -- if you lost sales, how much
7 does that matter? Well, that depends on your margin.
8 That's the effect on your profits. It would be how many
9 sales you lose and how much your profit margin was on
10 those sales. So, P_2 minus C_2 , P is your price, C is your
11 marginal cost.

12 So, this is the opportunity cost term. So, if
13 I sell one more unit, that's the cost in terms of profits
14 on your product, which is now internalized due to the
15 merger. So, that's one side of the equation. That's the
16 loss of competition. So, we actually then kind of have a
17 way to quantify that.

18 Now, what about the other side of it? Now,
19 here's the difference. In the merger guidelines, there
20 would be this whole work-up and then only at the end do
21 we say, oh, we figured out all this stuff, now let's
22 compare efficiencies. So, one of the other tricks here
23 is we say, no, no, no, what we should be doing is we've
24 got to -- basically, the merger we can think of as like a
25 cost increase for the product I'm selling. It's an

1 industry or type of merger or something. But that's a
2 level of sophistication I don't want to get into, just
3 the same way we don't have different Herfindahl
4 thresholds for different industries.

5 So, again, don't think of this as a complete
6 analysis, think of it as supposed to be uniform, simple,
7 transparent so that companies can rely on this. So,
8 we've got a policy parameter, E.

9 One of the differences here, though, as you can
10 see is, look, at least we would know what empirical
11 evidence to look at to figure out what E should be. I
12 guess you would know what to look at to figure out the
13 Herfindahl 1,800 and the change of 200. I haven't seen a
14 lot of studies that really tie that down for me, why
15 that's 1,800 and the change is 100.

16 Here, I'm not saying it's going to be easy, but
17 this is what you really care about. What has actually
18 happened when firms have merged? What sort of
19 efficiencies have they achieved? That would be built

1 of algebra. But this, I think, is helpful for getting a
2 sense of the calibration of the test.

3 So, for example, if you had a margin of one-
4 third, not an unreasonable margin in a lot of industries
5 -- it could be much higher in some industries -- if you
6 were willing to spot 10 percent as your efficiencies
7 associated with the merger, then, in that case, you would
8 get upper pricing pressure if the diversion ratio was
9 greater than 20 percent. You got a symmetric situation.
10 You can put in other numbers. The paper has more
11 formulas and examples.

12 So, now, we have a theorem. Even though it's a
13 policy paper, we have theorem. So, I'm going to now say
14 if this inequality is satisfied, I'll say there's upper
15 pricing pressure for Product 1. Okay, let's define that.
16 The theorem says, if there's upper pricing pressure for
17 both products and they merged and the merger caused the
18 default or assumed level of efficiencies, both prices
19 would go up in a Bertrand duopoly. So, that's the
20 specific model that sort of underlies the logic here.

21 Now, I know very well, and you do, too, and we
22 heard earlier today, not all these margins are going to
23 be Bertrand duopolies. But this is -- and I will talk
24 about that, too. But this is the simple logic underlying
25 this in theorem form.

1 The concept, I think, is very robust. You
2 know, loss of direct competition compared with
3 efficiencies, but to actually come up with an operational
4 test, one does need to make some additional assumptions
5 and we've got that here.

6 Now, this does not say how much the price is
7 going to go up. I didn't say anything about pre and
8 post-merger equilibrium. I just said the price will be
9 higher. So, that's the result. So, that's where we're
10 going.

11 Now, let me detour a little bit and say -- some
12 of the objections we've gotten to this over the past
13 half-year or so when we've been kicking it around. Some
14 people say, well, okay, you've got actually a very
15 convincing logic that if that test satisfied, prices will
16 tend to go up, but they might not go up by much. So, is
17 that too harsh or is that too quick to reach a
18 presumption?

19 So, our answer to that is, no, we've thought
20 about that. And I may or may not convince you on this
21 point, but here's our response, which is, we've spotted
22 the firms with default level efficiencies. I mean, so,
23 we're already building in the notion that the loss of
24 competition is significant in the sense it's more than we
25 would credit with efficiencies.

1 And if you take the strict consumer welfare
2 standard that's in the guidelines, I mean, the guidelines
3 say, for example, the snip -- the amount of the snip -- I

1 the underlying principle here is very general. That if
2 costs go up, prices will go up.

3 We're also not trying to predict the entire
4 model of what determines pre-merger prices. This is one
5 of the difficulties with merger simulation. You try to
6 come up with a model in terms of all the pre-merger
7 prices and then change the parameters. We're just
8 focusing on the change, which is what we care about. All
9 sorts of things go into the level. I don't know about
10 that stuff. It's very complicated. But the change we
11 actually can hone in on and we do that. And we're not
12 drawing boundaries or setting up these algorithms such as
13 one sees in market definition.

14 The test actually is very general with respect
15 to the shape of the demand system. And those of you who
16 are familiar with Greg Werden's 1996 paper, there's a
17 very close relationship here. I'll glide over that in a
18 moment.

19 Market definition and merger simulation both
20 depend on the demand shape. We don't need that at all
21 here. That's the big advantage of not caring about -- I
22 shouldn't say not caring, not trying to estimate
23 magnitudes, but only directions.

24 We also don't actually need static Bertrand.
25 The paper explains this, and there's another paper Joe

1 and I wrote earlier this year about critical loss. If
2 the behavior is non-Bertrand, what you do is you figure
3 out the diversion ratio, the real-world diversion ratio,
4 we call the residual diversion ratio, which is against
5 the residual demand curve.

6 If I move my price, you may accommodate --
7 suppose I raise my price. You're going to accommodate
8 your price, let's say. That's going to mean a lower
9 diversion ratio. Suppose you accommodate or a small
10 group of people accommodate, but some other people
11 further afield don't change their prices. Then less of
12 my diversion will be to you because we're moving prices
13 and more from outside.

14 So, the way to -- so, you can build that in
15 easily by correctly defining the diversion ratio based on
16 the real-world behavior. So, it's actually very general
17 with respect to oligopoly behavior as well as demand
18 shape if you recognize the diversion ratio needs to be
19 what I call the real-world diversion ratio, which is if
20 I'm contemplating a price move and the responses that are
21 really going to happen, what sort of shifting around of
22 sales will occur? And that's something for you to do in
23 the real world.

24 That's the other thing. We think this is
25 actually easier to implement than what's being done now.

1 You've got to measure price and marginal cost. This is
2 already done in mergers because you're figuring out
3 margins, you do it for critical loss. I know
4 econometricians tend to think, oh, well, the way -- I'll

1 business documents about who they're gaining and losing,
2 win-loss reports, you know, those sort of things really
3 come up without getting into some artificial exercise of,
4 if all these prices went up, what would you do or what
5 would happen?

6 When you ask customers these things, they often
7 scratch their heads and say, that's kind of a strange
8 question. But if you ask them if this guy raised his
9 price, what would you turn to? They're like, oh, well,
10 that happened or I've thought about that, here's my
11 second choice. You're much closer to the real world.
12 So, it makes easier to get accurate information.

13 There's not many things that need to be
14 measured here. And you don't have all this stuff about
15 should you measure things in units or dollars or -- you
16 know, all this peculiar stuff that comes up with market
17 definition and shares that's kind of artificial. None of
18 that.

19 To the extent you're relying on actual normal
20 course of business documents about margins and diversion,
21 this reduces the scope for game play and litigation.
22 Because you're not asking a new set of questions only in
23 this context. You would look at how the company's
24 actually running their business which, of course, is the
25 preferred type of evidence in any antitrust case. But

1 you're really going for that here directly.

2 We think it's transparent. There has to be
3 some work done to explain this logic to judges and to the

1 the companies, who think about it in court, would say,
2 you know, you measured the margin wrong, you got the
3 diversion ratio wrong. There's some other factors going
4 on in your test. And that would be called direct
5 rebuttal. That's, of course, defined. And then if the
6 companies can't rebut on that, then you move to the full
7 analysis of competitive effects in the back end just as

1 In many ways, I'm a big supporter of the
2 guidelines. Well, I think in '92 or I'll even go back to
3 '82, you know, big steps forward, big steps forward. But
4 we have had 15 plus years of experience with these now
5 and there's a problem in this area. I think a lot of
6 people recognize it. So, not to throw them out, but to
7 amend them and -- so, I'm hoping this -- we're hoping
8 this will trigger that debate in a substantive way, but
9 not in the sense of, oh, it's a big change, so we
10 couldn't do it and sort of stop there.

11 And that goes back to the first set of
12 responses. Is it really a big change at the agencies?
13 I'd be curious what people think. It would certainly --
14 you know, it would be a change for the courts. They'd be
15 getting a different message. And hearing what I heard
16 this morning about Brown Shoe and so forth, you know, I
17 don't think it's necessary to -- one doesn't have to skip
18 market definition.

19 Take Whole Foods. I think if you would do
20 this, you'd say, look, the market -- we don't really
21 care, basically. The reality is it's either a really
22 concentrated merger in a narrow set of firms, a premium
23 national organic supermarket, or not very concentrated in
24 a broader set of firms. But in that case, it's two firms
25 who happen to offer very head-to-head -- products that

1 are quite close to each other within that broader market
2 because of the product characteristics. So, we don't
3 really care.

4 If you want -- if the merging parties want and
5 the court wants to pick the broader market, go ahead,
6 pick the broader market because we're not trying to get a
7 presumption based on the shares in that market. So,
8 we'll look at that market and we'll agree that looking at
9 the dynamics and the trends of what's going on in that
10 market is a good thing to do, particularly as it relates
11 to diversion between the two firms, between the two of
12 them.

13 So, don't get hung up on the market definition.
14 Define a market, get over it, and then go forward. And
15 then, true, you'd have to explain how can it be that it's
16 causing problems even when it's only -- I don't know what
17 it would be in that market. I don't know the numbers.
18 Five percent plus 3 percent or something. I don't know
19 if I'm close. You say, well, that happens when you've
20 got these circumstances. And for better or worse, I
21 think Brown Shoe helped put that point, although I don't
22 really quite go there.

23 So, that all seems like it could be practical.
24 But, of course, it would require revising the guidelines
25 because the agencies couldn't very well go and do that in

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1 a little more about Oracle and Whole Foods and so forth.
2 There's going to be a panel at the ABA spring meeting,
3 actually, on possibly revising the guidelines.

4 I get there by looking at specific examples of
5 where I think it's most clear that the problems are
6 arising. I'm not sure exactly how else we would prove
7 it. I think there's general grumbling I hear around, but
8 that's a proof.

9 AUDIENCE MEMBER: One sense in --

10 MR. SHAPIRO: Let me just say one other thing.
I think part of the problem is a lot of what goes on

1 hung up on this point about, well, if you say these guys
2 are going to raise price, then that should be a market
3 and just got kind of tied up in that. So, I think these
4 are very practical problems that are inherent in the
5 current structure of how it's done.

6 MR. SCHMIDT: Okay, thanks, Carl. We're a
7 little bit behind time now. So, let's take like five
8 minutes to give people a chance to throw stuff away and
 stretch their legs and otshotDahs0fgch rfhesesD32hmarket

1 A E. E. : BE A. A A D E E. E A EC. C

2 MR. LIST: So, good afternoon. I'd like to
3 introduce Paper Session Two, which is about Behavioral
4 and Experimental Economics.

5 And we're going to do something different here.
6 There isn't a typo in the program. Rob Letzler will be
7 discussing all four papers. And we're doing that on
8 purpose because we added one extra paper to this session.
9 When we put out the call, we received a lot of paper
10 submissions for this particular session and there were a
11 lot of very good papers. So, we decided to accept four
12 rather than three. But as a compromise, Rob will be
13 commenting at the end of all four papers about his
14 thoughts on each of the papers, in particular.

15 So, after each talk, I will ask you if you have
16 any pressing questions, and if you don't, we will move on
17 and then take all questions at the end.

18 So, I'd like to start with introducing Stephan
19 Meier, who I view as one of the top experimental and
20 behavioral economists, not only in the U.S. but in the
21 world. So, thanks a lot, Stephan, for joining us and
22 you're up.

23 MR. MEIER: Thank you very much for the nice
24 introduction and it didn't help reducing my being
25 nervous. But anyway...

(.)

1
2 MR. MEIER: So, I'm happy to present this
3 paper, which is, as you see from the title, it's about
4 present-biased preferences and credit card borrowing.
5 It's jointly with my former research assistant, Charles
6 Sprenger, who is now conducting a Ph.D. at UC San Diego.

7 So, just to start, I'll give you two facts
8 which are going to be important about credit card
9 borrowing. First, it's important in size. So, the U.S.
10 population borrows a lot. If you just look at self-
11 reported data from the Survey of Consumer Finance, they
12 borrow about \$30,000 on the average in non-mortgage debt,
13 about 20 percent of that on credit cards, and that's
14 going to be for sure a lower bound because we know that
15 people normally under-report their debt by a factor of
16 two or three, or they outright lie about what kind of
17 debt they actually have. So, it's going to be important
18 for our project because we're not going to look at self-
19 reported data.

20 The second fact is there is large heterogeneity
21 between people in borrowing on their credit cards. So,
22 again, if you look at the Survey of Consumer Finance,
23 only about 60 percent of people who have a credit card
24 actually carry a balance on it. And our paper is we
25 wanted to explain some of this heterogeneity by focusing

1 in particular on time preferences, on impatient and
2 present-bias preferences.

3 Now, what do I mean with impatient and present-
4 bias preferences because I use them very loosely? So,
5 what I basically mean is with impatient, that what we
6 normally write in our model, that's the exponential
7 discounting factor. So, that's how much people care
8 about the future.

9 Now, the second one, the present bias, is there
10 an extra weight on the present when faced with
11 instantaneous gratification? And if you think about the
12 quasi-hyperbolic model written down by, for example,
13 David Laibson, you can think about the discounting factor
14 as the delta and this (inaudible) factor into present
15 bias as the beta which weights, basically, the whole
16 discounting function a little bit downwards at the
17 beginning.

18 So, what are the effects of present bias
19 theoretically? I mean, first, they value the present so
20 much, it will lead to dynamic inconsistency. So, people
21 might make a plan for how they discount in the future,
22 but when the future becomes the present, they violate
23 that plan and become suddenly more impatient. That might
24 lead to over-borrowing, given their long-run plans. So,
25 they want to borrow actually less, so that's what they

1 plan, but then they borrow too much.

2 There is a bunch of evidence from laboratory
3 studies that, in fact, people do discount extra -- have
4 like this extra weight or have like present bias
5 preferences. There is a survey in the Journal of
6 Economic Literature that shows that, well, there is a
7 large fraction of people who discount with this present
8 bias parameter.

9 There are also some new economic studies which
10 can tell you a little bit of a story of where that might
11 come from. So, people might have like two systems,
12 decision-making systems in the brain. One is known as
13 the deliberate system. So, you plan, you think about the
14 future. And the other one is more of an effective system
15 which gets triggered when there is this instantaneous
16 benefit.

17 Laibson and coauthors show that, well, if you
18 put people in a scanner and confront them with choices
19 very similar to what we confront them with is, if there
20 is this instantaneous benefit, this more effective system
21 actually gets (inaudible).

22 So, obviously, this has an important
23 implication for IO, how competition works and for public
24 policy, how we think about how to regulate it. However,
25 and this is the prime example -- one of the prime

1 examples in behavioral economics, present bias leads to
2 more credit card borrowing.

3 Now, the evidence is actually not so great on
4 that issue. And here are two kind of basic empirical
5 approaches so far. One is you take aggregate data and
6 you try to match the moments in that data with each an
7 exponential or a quasi-hyperbolic function. So, for
8 example, Laibson looked at, well, how can you explain
9 credit card borrowing on one hand and holding of liquid
10 assets on the other one, and you're doing a pretty bad
11 job exponentially. You'll do a little bit better if you
12 fit like a quasi-hyperbolic where it has like this
13 present bias parameter (inaudible).

14 This is great evidence on the aggregate.
15 However, you want to see on the individual level whether
16 those people who are present bias actually have more
17 borrowing. So, that's why experimental economists
18 measure (inaudible) references directly and report it so
19 far and correlated it so far as to self-reported measures
20 of spending patterns, for example.

21 So, Harrison did, in Denmark, a study where he
22 mainly cares about this long run discount effect. So, he
23 doesn't really look at present bias. He looks at long
24 run discount effects and sees whether people report that
25 they have debt on their credit card. It doesn't

1 correlate in their study. So, long run discount factor
2 in Denmark seems not to be correlated with whether they
3 have any credit card borrowing, self reported.

4 The second one is a paper in Germany where they
5 do very similar measures of time preferences as we do.
6 So, they are able to distinguish who is actually present
7 biased or not and find out that those who are present
8 biased claim that they have more problems with spending.

1 in explaining who actually borrows and who doesn't.
2 However, present bias is associated with debt problems,
3 and people who are present biased borrow substantially
4 more. This is particular strong for those who actually
5 have a credit card. And Dean probably talks more about
6 commitment devices. That might be one indication, well,
7 there might be some present biased guys around who
8 figured out, well, not having a credit card is actually
9 good for me. So, we can distinguish a little bit there.

10 So, I'm going to talk about the setup, the
11 results and then I'll conclude. So, what is the setup?
12 We do this study in what is called a voluntary income tax
13 assistance site. So, this is volunteers help earned
14 income tax credit recipients fill out their taxes. So,
15 they come into those tax sites. There are about 22 in
16 the Boston area, and it's run by the City of Boston and
17 the Federal Reserve Bank together, and they come in and
18 they get offered a credit report. And volunteers
19 actually help them a little bit understand what is in the
20 credit report.

21 We independently measure individuals' time
22 preferences with choice experiment, and I'm going to
23 explain in a second what we do. And then we match this
24 credit data with time preferences, and because it's in a
25 tax site, we also have their tax data. So, we also match

1 it to their tax data.

2 This was done in two neighborhoods in Boston,
3 Dorchester and Roxbury. In two years, we got about 600
4 individuals, and for about 540, we had usable matches of
5 time preference.

6 Obviously, this is not a representative sample,
7 in various respects. One is, they're low to moderate
8 income people. They earn about, on average, \$18,000
9 after tax per year. So, they're extremely, extremely
10 poor. You have to take that into account when we
11 interpret the sizes of the effects.

12 I think it's more a feature than a problem
13 because we care a lot about people of low to moderate
14 income, because if they make mistakes, it has
15 catastrophic consequences, while if I do -- and I do a
16 lot of them -- it doesn't matter that much. And there is
17 also this growing market for marginal or subprime
18 borrowers, and we are interested in what happens there.

19 There is an additional selection effect and
20 that is -- so, remember, they come in and we offer them a
21 credit score. Not everybody takes the score and we only
22 observe those who actually have scores. So, we also --
23 we measure time preference for everybody and see who's
24 selected to that program or who is in our sample. And
25 you see that they're actually more patient, they're more

1 sophisticated guys. So, we should also keep that in mind
2 when we try to generalize from our results to the general
3 population of low to moderate income people or to the
4 general population.

5 The data comes from one of the credit bureaus.
6 As I said, we get their report. The most important
7 information we use on the report is the amount of
8 revolving accounts. Those are mainly credit cards. Now,
9 if you're familiar with credit reports, that's not debt,
10 per se. That could be convenience charges. We don't
11 know how much of that is actually debt. What we do --
12 because the Survey of Consumer Finance asks the question,
13 at the end of the month, what do you normally do? Do you
14 pay off the whole amount of your balance or just a
15 fraction and so forth? So, we can look at whether those
16 people who say they pay off the full amount, whether they
17 have actually much more amount on their revolving
18 accounts and they actually have.

19 You can do the same analysis as I showed you
20 here for the question on who pays the full amount and the
21 results are the same. But we're going to look at the
22 amount for lower income.

23 There's also information on credit constraints.
24 I mean, we know the limit and we know how much they used
25 of that limit. So, we can control whether our measure of

1 -- in the choice experiment has actually anything to do
2 with the credit constraint (inaudible).

3 So, here is what we do. We ask them a bunch of
4 questions. Do you want to have a smaller amount now or a
5 little bit of a bigger amount in the future? So, they go
6 through that list. So, where we ask them \$75 today
7 versus \$80 in a month, what do you want? Then we ask
8 them the second question and so on.

9 We ask them a bunch of those questions.
10 Importantly, we ask it in the three different time sets.
11 So, we ask them, today, one month, that was the example I
12 just showed you. Then we extend the period. We say,
13 today, six months, and then we shift the whole period
14 into the future and say, okay, six and seven months. And
15 we use that to estimate or to measure the structure of
16 their time preferences. So, a typical present-biased guy
17 would be very patient in the sixth and seventh month, but
18 if the present was involved, he gets very, very
19 impatient.

20 Now, you might say, well, that's just because
21 in the present he actually gets it right now and in the
22 other one, he gets it by mail or whatever and there is
23 some uncertainty involved. Well, we tried to get rid of
24 that. Actually, in both cases, he or she gets the
25 payment by mail. So, we mail it either today and he or

1 she gets it tomorrow, or we mail it in a month or in six
2 or in seven months. Just to keep transaction costs
3 between those two things very similar. We can also look
4 whether they expect to move and it doesn't matter.

5 So, we pay -- about 10 percent of the
6 participants get paid. And then we can measure this
7 individual discount factor, which is what I called before
8 impatient, and we can see whether people are dynamically
9 inconsistent in those two choices and we use -- in the
10 baseline, we use just a dummy, whether they are present-
11 biased or not. You can also fit a data delta function
12 through the choices. Even though it doesn't fit exactly,
13 the pattern in the data, you can do it and the results
14 are the same.

15 Now, you might say, well, well, well, what they
16 tell you in those choice sets might have a lot to do with
17 like their credit constraint, which is going to be a
18 problem here. Now, first, others have shown that using
19 those payments to measure time preferences is actually
20 highly correlated to either using primary rewards. So,
21 instead of giving them a little bit less money now or a
22 little bit more tomorrow, you can give them a little bit
23 less chocolate now and a little bit more chocolate
24 tomorrow or choose (inaudible) they are heavily
25 correlated.

1 You can also look at response rates. So, if
2 you go through that list, there are like choices which
3 are simple. But the closer you get to that indifferent
4 point, the harder it gets to answer the question. So,
5 you can measure how long individuals take to make those
6 choices and that's highly correlated with the measure you
7 get when just using the one (inaudible).

8 AUDIENCE MEMBER: I have a clarifying question.

9 MR. MEIER: Yes?

10 AUDIENCE MEMBER: (Off microphone) Are you
11 doing this by computer and that's how you can measure how
12 long it (inaudible)?

13 MR. MEIER: Well, they do, we don't. I mean,
14 that's another paper.

15 AUDIENCE MEMBER: (Off microphone) (Inaudible).

16 MR. MEIER: Yeah, so what we do -- so, these
17 are other papers. What we do is we can look does present
18 bias correlate with their credit limit? On their report,
19 it doesn't. For a subset of people for the 2006 sample,
20 we also get their credit report one year after the
21 experiment. So, we measure their preferences today and
22 then see whether we can predict how much revolving
23 balance they have one year later, just to get a little
24 bit rid of that mighty shock (inaudible) and the results
25 hold. And you can just -- in all the regression, you can

1 control for a limit and their FICO score and -- one or
2 the other, and the results are not affected.

3 So, what are the results? So, what you see
4 here is outstanding balances -- these are the raw
5 correlations. Outstanding balances whether they're
6 present biased or not, and you see that there's a
7 substantial difference of about \$700 in what present --
8 and, remember, they have \$18,000 in disposable income per
9 year. So, we think that's a substantial difference in
10 what present biased guys carry on their credit cards and
11 people who are not.

12 Now, you can control -- if you basically look
13 at column two, where we control for some social
14 demographics, in particular income, the number of
15 dependents. That's from the tax information, their
16 educational level and some demographics. And you see,
17 first, that the individual discount factor, that's
18 basically the exponential discount factor we normally
19 write down in our models. It doesn't do anything to
20 their borrowing. Very similar to what Harrison found in
21 his study in Denmark.

22 However, if you look at the present bias,
23 present-biased individuals carry higher debt on their
24 revolving accounts. Those are two (inaudible) so it's
25 hard to interpret. If you knew the marginal effects here

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1 you might be worried -- well, you might pick up some of
2 the curvature of the utility function in those choices
3 and not just time preferences. It could be a question on
4 the risk attitude and you can control for that. You can
5 control for whether they expect to move, because he might
6 say, well, you ship it, but it might be a problem if they
7 expect to move in six months, that the probability that
8 they actually get it is very different between the
9 different choices.

10 We can get (inaudible) and include multiple
11 (inaudible). I hadn't talked about that. For some
12 people, that's very hard to calculate time preferences,
13 because what they basically do, they switch around. So,
14 they say like, well, 75 over 80, well, I'll take 75, and
15 then what about 70 over 80. I'll take 80. And 65 over
16 80, well, 65. So, they seem to -- I don't know exactly
17 what they do. You can take their first switching point
18 and assume that's really the one they wanted to and the
19 results are the same.

20 Again, as I said, it's very important for one
21 sample, we looked at their borrowing one year later, the
22 results are the same.

23 So, let me conclude. I think we tried to
24 combine experiments in the sense that the methodology
25 from lab experiments to measure people's time preferences

1 present biased know that they're present biased and take
2 actions to limit their vulnerability, so to speak, from
3 them? So, thank you very much.

4 (A .)

5 MR. LIST: Okay, very good, thank you, Stephan.
6 Are there any pressing questions at this point or can we
7 move on?

8 (.)

9 MR. LIST: Okay, great. James, why don't you
10 come up and load. I'll give just a brief introduction.

11 So, our next paper is by James Hilger.
12 Obviously, I just met James today. And he is talking
13 about an experiment that he's run in one of my favorite
14 markets, the retail wine market. So, he'll talk for a
15 bit, and if there are any questions, I'll take those at
16 the end.

17 MR. HILGER: Thank you. Thank you, everyone.
18 First, I have two housekeeping things I need to take care
19 of. One is that I have the typical FTC disclaimer.
20 These are the views of my own and don't represent the
21 Commission or the Bureau. And the second is that if you
22 have a copy of this paper, today, I'm going to present
23 recent results. They are qualitatively the same. So, if
24 you get lost, if you're flipping through the paper,
25 that's why.

1 So, I'm going to talk, as John said, about
2 expert opinion labeling in the wine market. So,
3 experience goods are goods that are defined as products
4 or services that you don't know the quality of that
5 product or service until you've actually consumed it.
6 And in today's marketplace, there are a lot of goods, in
7 fact, one might say most goods, that you really don't
8 have a sense for what you got until after you've had it.
9 Wine is an example.

10 Books could be an example. A dinner could be
11 an example. And you could stretch that to some of the
12 things I work at here, major appliances or lightbulbs.
13 One might not know the impact of a purchase on their
14 electricity bill until after they've bought that product
15 and experienced the good.

16 So, there are a lot of areas where consumers
17 rely on the opinion and information provided by experts
18 to make their decisions, and I'm going to look at the
19 wine market, specifically.

20 First, a little background, Jen and Leslie have
21 a paper that looks at the impact of restaurant sanitary
22 quality postings. And they found that consumers respond
23 to the higher-quality, A-grade restaurants. But this
24 paper doesn't really get at some of the aspects of what I
25 want to talk about. It's hard to separate out the

1 information -- the actual provision of information, the
2 quality that's posted and the actual quality of the
3 restaurant.

4 There are a lot of different sources of
5 information that consumers might be using to decide if a
6 restaurant is of high quality or low quality besides just

1 which scores were available. So, I just want to point
2 that out.

3 As I mentioned, we have a lot of different
4 control stores. This is a unique problem that in the
5 dif-dif literature, you know, we had more stores than we
6 wanted to use. The stores were all in the same
7 geographic area, but, you know, they had differences in
8 sales. So, we wouldn't necessarily want to pool all of
9 the stores together because the consumers in different
10 stores might be systematically different.

11 So, to select our control store, we went
12 through several different analyses. One just looked at
13 the demographics of the consumers in the area, of the
14 store. We also ran estimated demand -- reduced form
15 demand equations and then did Chow tests for pooling, and
16 we also looked at if the store sales across stores moved
17 in parallel over time.

1 time, I'm going to skip through that. I do want to note
2 that in this slide K would be whether or not the actual
3 wine was labeled. So, we have T is a dummy for the
4 treatment time period; J being the treatment store; K
5 being a wine that was actually labeled. And this dif-dif
6 analysis we did over two time periods, not the two years,
7 but two months.

8 AUDIENCE MEMBER: (Off microphone) Can you tell
9 us why you'd need a regression if you have an experiment?

10 MR. HILGER: Good question. The question was,
11 why do I need a regression if I have an experiment?
12 Because there are some covariates and when I include
13 those -- so, the first model is just basic dif-dif and
14 dif. And when I move on, we'll find the impact of the
15 heterogeneity in one of the covariates.

16 AUDIENCE MEMBER: (Off microphone) (Inaudible)
17 experiment or (inaudible)?

18 MR. HILGER: It's a field experiment.

19 AUDIENCE MEMBER: (Off microphone) Wouldn't you
20 randomly assign (inaudible) information on pricing
21 conditions across bottles of wine?

22 MR. HILGER: Correct.

23 AUDIENCE MEMBER: (Off microphone) So, why
24 don't you just do it with (inaudible) across different
25 bottles of wine and you don't have to worry about doing

1 (inaudible)? I guess that's what I'm -- it might be
2 useful to clear that up for the audience.

3 MR. HILGER: Okay. The question is, why don't
4 we just compare -- you know, put the expert opinion label
5 up and then look at the impact in the one store between
6 wines that were sold and wines that -- I mean, wines that
7 were labeled and wines that weren't labeled. Well, one
8 thing is if we did that analysis, we wouldn't be -- we
9 might find a shifting of the -- you know, if people --
10 you might find a switching effect.

11 Also, we wanted to control for previous time
12 periods and it's not clear to me, you know, at the moment
13 quickly how those -- the time switches and time trends
14 and trends across store might impact that. But, most of
15 all, we wouldn't be able to -- well, let's move on and
16 maybe address that.

17 So, the first results, on the left is a triple
18 difference and on the right is the dif-dif. So, in the
19 top red highlighted box, we have a store month effect,
20 which is basically did the treatment store sell more
21 wines in the treatment period compared to the control
22 store set, difference between treatment and control
23 periods. And we found that that was a positive and
24 significant effect, which was, you know, to be clear,
25 somewhat worrisome because this is the effect, including

1 the effect on wines that weren't treated.

2 So, the treatment store and the treatment
3 period saw a relative increase in sales, even on the
4 untreated wines.

5 We have a positive effect insignificant on
6 label, store and month, which are the treated wines.
7 I do want to note that less than 1 percent of the K dummy
8 -- of the L -- I mean, this label, store, month variable,
9 less than 1 percent are one. So, you have a serious
10 power test and the probability of getting a T statistic
11 that significant is extremely low. But there is a
12 positive effect.

13 Then when we look at just the labeled wines, we
14 keep the positive effect on store, month. So, this is
15 just the labeled wines, but it's not significant. So,
16 the upshot is the average treatment effect on treated
17 wines is positive, but not significant.

18 Keith?

19 KEITH: (Off microphone) When you say labeled
20 wines, it's not information on the label, it's the one
21 you put a (inaudible) on?

22 MR. HILGER: Right. So, in this, we are not
23 controlling for the information yet, this actual score.
24 This is just it received a score.

25 Now, in the next model, we're going to include

1 some of the wine covariates, such as the actual score,
2 the price, and I'm going to note here that price is
3 always negative, because I have an interaction term and
4 it was easier to deal with that way, in a promo, whether
5 the wine was on sale, and a dummy variable for red wines.

6 So, I've run this several different ways,
7 building up from the most basic model and in several
8 different functional forms, quantity logged and not
9 logged and price and the score logged and not logged.
10 What we find when we include the score store month -- so,
11 this is the impact of -- the marginal impact of the score
12 on a treated wine in the treated store during the
13 treatment period is positive and significant for all of
14 those models.

15 Well, I should state that the average score
16 treatment effect is positive once you keep in mind or
17 take into account that the average score on a bottle of
18 wine was 84. So, if you calculate it out, you find that
19 the wines that, on average, you know, the high-priced
20 wines -- well, on average with an 84, there's a small
21 increase. But high-priced -- I mean, high-scoring wines
22 saw a large increase in sales of roughly -- well,
23 depending on which model you look at, you know, roughly
24 eight bottles. And I should have mentioned that the
25 average quantity sold was about nine bottles. So, they

1 saw roughly a -- not quite a doubling in sales, but they
2 saw a fairly large increase in sales.

3 In wines that received a low score, less than
4 70, saw a decrease in sales.

1 treated for the average wine, but scores that -- wines
2 that received a high score saw a significant increase in
3 sales and wines that saw a low score saw a negative -- I
4 mean, a negative change in sales.

5 So, this is -- you know, evidence points to the
6 fact that consumers could actually utilize the
7 information that's posted on the label, which is
8 interesting. You know, there's evidence that they're
9 basing their purchase decisions on information that's
10 provided, which was what we sought to investigate.

11 I think I'm out of time or over time, so I'll
12 wrap up now.

13 (A . . .)

14 MR. LIST: So, I'm going to go on because James
15 got a few questions from us that were sort of
16 spontaneous. But we'll come back to that one at the end
17 for anyone who has any other questions.

18 Our next paper will be by Cary Deck, who is a
19 dynamic, young experimenter from the University of
20 Arizona. Cary and I met at the University of Arizona
21 when I was a faculty member there. Cary will be talking
22 about price discrimination with sequential purchasing.

23 MR. DECK: Thank you, John. So, first, I guess
24 I should acknowledge that this is joint work with John
25 Aloysius and Amy Farmer, who are both at the University

1 of Arkansas with me.

2 The other thing I guess I should point out,
3 since everybody has gotten up here from the FTC and made
4 this big disclaimer of not speaking for the FTC, even
5 though our college is named I guess from a certain
6 Bentonville-based retailer and they have given large
7 amounts of money to both the CRE and the ITRI and the
8 college which funded this research, I, of course -- they
9 never talked to me.

10 (.)

11 MR. DECK: It would be nice, but they've never
12 talked to me, frankly.

13 So, this paper is a little bit different in
14 that I'm not trying to explain anything that I know is
15 going on currently, although it may be. I just have no
16 information on that. But I'm trying to be a little more
17 kind of forward-looking in thinking about what might be
18 coming down the road.

19 And, so, if you think about going through any
20 large retailer, the firms are currently using RFID
21 technology, little radio frequency tags, at the pallet
22 level to track kind of large shipments from the
23 wholesaler to the back room, putting them out on the
24 floor, and then when it goes to the crusher.

25 They're starting to include item level tags,

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1 these prices on different goods, within a shopping trip,
2 maybe it's not too hard online. You can track pretty
3 well what people have looked at, maybe where they've
4 searched, what items they've viewed and not put in their
5 shopping cart, what items they've viewed and had put in
6 their electronic shopping cart. In the store, it may be
7 a little more difficult, but there's new technology
8 that's coming along, like RFID, like this smart shopping
9 card, that would allow you to do more of this kind of
10 practice.

11 So, the idea here is there's this little
12 shopping cart add-on and you can see the price on any
13 item to keep a running total for you to throw it in your
14 basket. You can certainly envision a world where it
15 says, hey, we see you've just bought this, and like
16 Amazon, recommend some other products you might want to
17 buy. You've bought this, maybe you'd like that, too.
18 You've got four of the items for a lasagna, don't forget
19 you probably need to buy this item, too.

20 So, it's going to be possible to start tracking
21 these purchases as you move around the store and start
22 setting prices to individuals based on the items that are
23 in there. So, you can think about these little things
24 popping up, little coupons. And say, oh, this is great,
25 I've got a 50-cent off coupon when I approach the jelly,

1 that's wonderful. Not knowing, of course, that the next
2 person got \$1.50 off the same jar. I'm not going to be
3 mad, I got a coupon. They're not going to be mad, they
4 got a coupon. And we don't know that each other is being
5 treated differently here.

6 So, what we want to look at is to try to figure
7 out what the implications of this might be. So, sellers
8 now have large amounts of information on buyer
9 preferences. They get scanner data if you have frequent
10 buyer cards. We use credit cards. They can track your
11 purchases across time, everybody else's purchases across
12 time, and they can get a pretty good idea what kind of
13 goods have what kind of relationship with each other,
14 whether or not the values of particular goods are highly
15 correlated or not, whether or not the goods are
16 compliments or substitutes or not. And, of course, those
17 concepts -- sometimes when people think about them, they
18 view them as the same, but they're very different
19 concepts. It can be correlated, but not be complementary
20 or substitutable and the opposite is true as well.

21 So, traditionally, what sellers have had to do
22 is basically set their price in advance, but now we're
23 thinking about what happens if the seller can adjust
24 those prices in real-time. If we want to think about
25 what monopolists might do in this situation, it's kind of

1 a nice standard starting point for thinking about
2 pricing. And we want to think about what might happen in
3 more competitive markets with this kind of ability.

4 So, traditionally, in what you could also label
5 as pure components, the sellers maybe know the
6 distribution of buyer types and they set optimal prices.
7 They're going to post prices prior to the buyers coming
8 in and observing and making that purchase decision. So,
9 the seller is going to attempt to increase profits by
10 doing price discrimination like quantity discounts,
11 coupons, all of these types of things. They're kind of
12 more generally applied.

13 Another technique, at least in thinking about
14 combining different items, is mixed bundling. So, what
15 you do is basically sell the components by themselves and
16 allow the person to buy the bundle of the two goods. So,
17 going back, you know, for a long time we've known that
18 you can generate increased revenue, at least if you're a
19 monopolist by basically jacking up the price on the
20 single item and then cutting people a break on the
21 bundle. So, this is a technique that people use to try
22 to -- sellers use to try to increase those revenues.

23 There's a recent paper by Venkatesh and
24 Kamakura where they try to basically go back and redo the
25 Adams and Yellen type of setup where they exam explicitly

1 kind of the degree of complementarity, that theta there,
2 the degree of complementarity between the individual
3 items that are being bought. So, there's good A and
4 there's good B. The buyers have values for those single
5 items and then they have the value of the bundle from
6 buying both items that some combination or that some
7 multiple of the sum of the single item prices.

8 So, we're going to follow along this --
9 ultimately, we're going to follow along this same kind of
10 model structure here and trying to think about how
11 sequential pricing might influence the market.

12 So, with sequential pricing, just a little
13 example to drive home what we're saying here. So, the
14 seller actually can set prices incrementally during the
15 shopping trip. And they're setting them to a specific
h iteat we're saying h18.sauF8tTm15

1 that's the end of the story. They're going to expect to
2 make \$100. They don't know which type of buyers is
3 visiting. They could drop the price to \$20 and guarantee
4 selling to everyone, but that's lower -- guaranteeing \$20
5 is lower than getting \$100 on average.

6 With mixed bundling, the result's the same,
7 because there's not these people who have high values of
8 one good and low values of the other good that you can
9 kind of exploit. It ends up being that this mixed
10 bundling would generate the same level of profit.

11 But if you could price them sequentially, you
12 walk in, you've got a price of \$100 on the first good.
13 Buyers say, yeah, I'm going to take that; no, I'm not
14 going to take that. A person who takes it, boom, you
15 know what they're willing to pay on the next item and you
16 can charge them a high price, whereas the person who
17 refuses to buy it, you can then charge them a lower price
18 on that second good.

19 Now, there's a clear assumption here which is
20 that you're preventing them from knowing the second price
21 until after the first price has been revealed and they've
22 actually made that decision. So, we're assuming that
23 they have, in fact, committed themselves to buy the good
24 once they've taken it, before they see the second good's
25 price.

1 So, with sequential pricing, it's still not the
2 condition that you've got to have discrimination going in
3 that second market. There may be some information that's
4 revealed to you that you can just use that you would
5 charge to all buyers in that second market there. But,
6 basically, the seller posts a price for good A; the buyer
7 makes a purchase decision on good A, then the seller is
8 going to set the unconditional price of good B,
9 unconditional in that it's not based on whether or not
10 the buyer purchased good A, and then the buyer can make
11 the purchase decision for good B.

12 So, a good, standard monopoly story, you go to
13 the end, the second good market. The seller knows that
14 some people have already bought A, some people have not.
15 They may have different values, depending on the theta
16 that's there, if these goods are complements. People who
17 have bought the first good are going to have kind of a
18 higher distribution of values for the second good.

19 And then, based on the answer there, given this
20 optimal second stage price, back up and figure out what's
21 the optimal price to set in the first stage. Of course,
22 here, what the seller is trying to figure out is, I'm
23 going to set my first period price in such a way that I
24 can -- I get the maximum exploitation at the second
25 stage. So, if I'm worried about the profit on this good,

1 but I'm also taking into account how I'm going to exploit
2 them next time based on what they do here or based upon
3 how their values might change.

4 AUDIENCE MEMBER: (Off microphone) When you say
5 in stage three unconditional, you mean you're going to
6 set the same price to all consumers, but we're going to
7 condition it on the information that (inaudible)?

8 MR. DECK: Well, what I mean here -- what I
9 mean here is that they're setting the same price for
10 people who did and did not buy the first good.

11 AUDIENCE MEMBER: (Off microphone) That's all
12 you mean by --

13 MR. DECK: That's all I mean by this.

14 AUDIENCE MEMBER: (Off microphone) (Inaudible)
15 using the information you know (inaudible)?

16 MR. DECK: You know about the information on

1 So, to go any further than that, we need to
2 make some kind of assumption on the distribution of
3 values. None, in particular, seems to jump out to me
4 empirically as something great from the current markets.
5 But a uniform distribution is a nice convenient trackable
6 way to start. So, this is a general assumption we're
7 going to make.

8 So, if we assume the values we just distributed
9 uniformly kind of over that square, we can work through
10 and determine -- you know, it's a long algebraic
11 exercise, but you can work through and determine what's
12 the optimal price to set of the second good, and given
13 that, what's the optimal price to set at the first good.
14 I don't show it up here because even in this simple
15 problem, it's -- just the answer is about a page and a
16 half long. So, there is a complicated answer one can
17 write up there.

18 Let me just point out if there's no cost, if
19 marginal costs, which is C , are zero and there's no
20 additivity in the products, then you've basically got two
21 unrelated markets and the firm ought to set monopoly
22 prices in both markets. So, that's that result.

23 If you can discriminate, now, step three
24 becomes that you're going to set a conditional price.
25 So, now the monopolist is facing these two concerns. One

1 is what price do I charge people who did buy the first
2 good and what's the price I should charge -- the second
3 problem is what's the price I should charge to anyone who
4 didn't buy the second good. And then given those, take
5 that into account in the first stage, they find the
6 optimal good A price.

7 Again, under the same uniform distribution
8 assumptions, this works out much nicer. You can figure
9 out what the optimal prices are at each point, for each
10 type of person. And, again, if there's no marginal cost
11 on the good and θ is zero, so the goods are just --
12 the value of the bundle is just additive, you would
13 charge the standard monopoly price in both markets. I
14 mean, there's no information coming in from whether or
15 not they bought good A or not. That doesn't tell the
16 seller anything.

17 So, what I did do is just kind of go through
18 and do some numerical comparisons for different θ s to
19 see what the implications -- so, we did some comparisons
20 to see what the effects of θ were. Basically, we
21 compare this with pure components, mixed bundling. It
22 turns out when the goods are substitutes, this kind of
23 practice can be very effective because, basically, it
24 prevents the buyer from substituting the first good for
25 the second good because you're kind of holding back the

1 second good on them.

2 We looked, also, at the correlation between the
3 goods. I'll say a little bit more about how we did this.
4 Basically, the distributions we used were just removing
5 the corners from that 100 by 100 square. So, if the
6 goods are highly correlated, like the example we showed
7 before, sequential pricing can outperform mixed bundling.
8 So, it can be an effective tool, but it's got to be at a
9 pretty extreme level before it beats something like mixed
10 bundling.

11 So, now, what we want to do is think about a
12 competitive market --

13 AUDIENCE MEMBER: (Off microphone) Before you
14 move on, are you assuming that buyers do or don't behave
15 -- are you assuming they don't behave strategically, the
16 buyers (inaudible)?

17 MR. DECK: In this case, they don't. The
18 buyers want a single unit of each good or, at most, a
19 single unit of each good. They're going to make one
20 choice. In the case of sequential pricing, they don't
21 know what prices are coming.

19f sequd. Ti5.7 -2firsTD(w, whastrat prices are co you)T

1 MR. DECK: So, one could think about how they
2 would react if they anticipated their decision at the
3 next stage. So, we could think about -- we're
4 abstracting away from that. We're just assuming they're
5 not. But you could think about this as a brand new
6 product, one they didn't even know existed, so they've
7 got no reason to be formulating a price expectation on
8 it.

9 In the interest of time, since I'm evidently
10 way behind, we're going to look at competition using
11 experiments, going to the laboratories, seeing how firms
12 might behave in this case. We're going to introduce the
13 idea of informed and uninformed shoppers. But,
14 basically, some of the shoppers know the price of good A
15 at every seller and some of them only go and visit one

1 very nice and very easy to explain to somebody who
2 doesn't understand what a joint distribution is and all
3 of this. We're going to draw from this.

4 A few other things. We've set marginal costs
5 to zero. We have four sellers in these markets. These
6 sellers are undergraduates who are in the role of a firm
7 and they're paid based upon the profits that their seller
8 earns. These took about 90 minutes. They ended up
9 making about 18 bucks. There was a lot more money at
10 stake for them. But as you'll see in just a second, they
11 were just very, very competitive.

12 These markets went very, very fast. The buyers
13 are assumed to be non-strategic. One buyer kind of
14 enters the market, reveals their decision and leaves.
15 So, the buyers are all automated. They're just
16 computerized. They show up every three seconds, see
17 the prices. Depending on whether or not they're informed
18 or uninformed make their decision and they leave the
19 market.

1 have complete information far more so than would occur in
2 a normal market -- in a naturally-occurring market.

3 So, just quickly kind of the base results here.
4 I'll just show the figures. There's econometrics in the
5 paper if you want all that detail. But, basically, in
6 the baseline case, the ability to discriminate doesn't
7 really seem to influence the prices that the sellers
8 charge. So, whether or not they're allowed to
9 discriminate or they cannot discriminate, it doesn't seem
10 to change what they're doing there.

11 The fact that they don't end up discriminating
12 based upon whether or not -- when they can, they don't
13 end up discriminating based upon whether or not the buyer
14 bought good A, which when θ is zero, they shouldn't.
15 I mean, there's no information in that and, therefore,
16 you wouldn't expect them to charge those buyers different
17 prices and they don't.

18 I'll just point out the ability to price
19 discriminate does not affect welfare here. But what you
20 can see is that the good A prices are way down low. I
21 mean, in fact, we have multiple times where people were
22 giving away good A because they were trying to capture
23 the good B market and get those comparison shoppers to
24 come to them. So, they were actually setting very, very
25 low prices on good A. And then, of course, where there's

1 no competition for good B for the sellers -- or for the
2 buyers who have come to them, they're charging much
3 higher prices. Theoretically, they should charge 50 to
4 everyone who comes to them, but they don't.

5 AUDIENCE MEMBER: (Off microphone) When you
6 started, my reaction was you must (inaudible) buyers, and
7 then when you go through it, it looks like you have
8 (inaudible) sellers. But I realized that you're giving

1 went through a lot of things there.

2 MR. LIST: On the other side, the comment was
3 you must have stupid sellers to do this, but then you
4 said, well, they only have three seconds to make up their
5 minds how they will price.

6 MR. DECK: Okay. They can adjust their price
7 at any point in time. Buyers show up every three
8 seconds. So, it's not as though, you know, Wal-Mart gets
9 a long time or anybody else gets a long time between when
10 people arrive at the store. I mean, they can adjust at
11 any point. They go for 750 periods. It's about an hour,
12 right? If you think about prices being set daily, this
13 is a couple of years' worth of experience greatly
14 condensed, but they also have a lot of information.

15 Now, the second part about whether or not they
16 price discriminate, well, in this market, they shouldn't.

17 If we do it to change when we have a comp (3) every 15, we can do A being hey a

18 till, the a lohoa clinection.1413

19 httllontiot or possibl time If ca: Ou think aion.

1 These experiments were far less efficient than with
2 bundling and the sellers made a lot more profit here than
3 they did with bundling. So, just to summarize, this new
4 technology could be very useful in a lot of ways, making
5 recommendations, providing new information.

6 It appears that the ability to discriminate is
7 going to kind of dampen the effect of doing this kind --
8 I'm sorry, the competition will dampen the effect of the
9 ability to price discriminate in such markets. But just
10 the ability to kind of price sequentially there may, in
11 fact, have harmful effects. And I will stop and answer
12 questions later.

13 (A .)

14 MR. LIST: Thank you very much, Cary. That was
15 very good.

16 Our last presenter is Dean Karlan from Yale.
17 Dean's a co-author of mine and one of a group of scholars
18 who is taking field experimental methods to important
19 issues in development economics. So, I think this is an
20 important line of research. So, Dean, fire away.

21 MR. KARLAN: Thank you, John. So, since I'm
22 last and shortened for time, I'm not going to actually
23 trim any slides. I'm just going to talk really fast.

24 (.)

25 MR. KARLAN: So this is joint work with Xavier

1 Gine and Jonathan Zinman. The heart of what we did is
2 really the perfect segue from Stephan's talk, the first
3 talk, Stephan Meier, about time inconsistency. What's
4 the implication from time inconsistent models whether
5 it's from -- any one of the kind of pick your model from
6 a theoretical perspective or we're talking about models
7 of dual self, hyperbolic models, quasi hyperbolic models,
8 whichever model you have that predicts or makes the
9 statement that there's some inconsistency over time in
10 the way people behave.

11 They all share a very common prediction, which
12 is that people should have a preference for commitment,
13 that when we look at the world around us, we actually
14 want certain things to cost us more money. And this is
15 not the normal way that we have traditionally thought
16 about a lot of situations.

17 You might actually -- different people might
18 have different facets of their life in which they have
19 this preference. You might prefer that peanut M&Ms cost
20 \$100. I know I do. Other people might just prefer that
21 the cost of debt was radically more expensive so that
22 they wouldn't borrow. But you don't control -- I can't
23 get M&Ms to jack up the price of peanut M&Ms. It's not
24 in their interest to do that. So, how does one go about
25 doing that and are there products that can be offered

1 individuals that effectively have that element to them?
2 That allow them to raise the price of things that they
3 want to be more expensive.

4 And, so, we did this with smoking. The very
5 simple question is, if there's people who want to stop
6 smoking, but they basically find themselves too tempted
7 in the future, and so, when the future is now, they end
8 up smoking. So, are there people who would say, you know
9 what, I would really like it if you could get cigarettes
10 to be more expensive?

11 Now, you can't actually go around and raise the
12 price of cigarettes except unless you're going to do it
13 through the government and do taxation. But, you know,
14 what is a private market solution to this is by having
15 people put up a bond, put up a contract that basically
16 commits them to stop smoking. So, I'm going to explain
17 how we go about doing this.

18 The one other element that Stephan referred to
19 as well that is a necessary element here, it's not just
20 time inconsistency, but there has to be an element of
21 sophistication. I have to not only want higher -- I have
22 to not only want to stop doing something or to start
23 doing something else, but I have to know enough about
24 myself to know that at the current price scheme, the
25 market prices that are going to be out there in the

1 world, that I'm going to screw up. And I have to be
2 sophisticated enough to want to actually change those
3 prices. That's a different element and that's not
4 something that's so obvious how we go about identifying
5 who's whom in that spectrum. Because, clearly, there are
6 going to be people who would be naive about this and
7 think that they will actually change their behavior
8 despite even if prices don't change.

9 So, I have skipped a whole bunch of stuff that
10 I will talk about. Other than to say I'm going to talk a
11 lot about smoking, because that's what this project is,
12 but the general concept can apply to savings, can apply
13 to borrowing, can apply to exercise, weight loss, voting,
14 and we actually have a Web site that we created in the
15 United States for doing just this, called STEKK
16 (phonetic), with an extra K. The extra K is for
17 contract.

18 So, what we did in the Philippines is we
19 created this product called CARES.

20 No, no, no, no, in legal -- that's what I'm
21 told. I remember this from being a child, taking notes
22 from my mother when she was in law school, that contract
23 is written with K in law school. So, the product -- I
24 told you, I'm just going to talk fast here now.

25 So, CARES is called Commitment Action to Reduce

1 and End Smoking. In the Philippines, acronyms are
2 popular for everything. Everything has to have an
3 acronym to it. Other things we've done are similar in
4 this spirit, that they always have these kind of catchy
5 acronyms to them. The commitment savings account we did
6 was called SEED.

7 So, you open up an account with 50 pesos, which
8 is \$1.25. We're basically dealing with people -- this is
9 not -- you know, it's a relatively poor area of the
10 Philippines, but this is not the poorest of the poor, by
11 any means. It's in the southern area of the Philippines
12 in an island called Mindanao.

13 A bank went out into the field and offered
14 individuals a bank account. And they said, look, here's
15 how this account works. You put in a dollar to start the
16 account. You have to do that. We will then come to you
17 every week and collect money from you and you're supposed
18 to -- we're going to give you a little box. This box
19 looks like this. This is where you're supposed to put
20 the money that you're putting into cigarettes, instead
21 put it in here. We'll come by once a week. We have a
22 little key for this box. We'll open the box up; we'll
23 empty out the money; we'll take it; we'll deposit it into
24 an account.

25 This box, to be clear, could easily be broken

1 with any simple sledgehammer type device. It's not a
2 foolproof system. It's just a mental account with a
3 small physical barrier.

4 Now, at the end of six months, the bank officer
5 comes back and has them take a urine test. If they pass
6 the urine test, they get their money back, zero interest.
7 The reason for zero interest is very simple. The bank
8 wouldn't do it with interest because -- why? Because,
9 otherwise, they'd be giving away a free deposit
10 collection service and they would have a bunch of people
11 who were not smokers taking this product up, and they
12 knew that that was just not the way to run this as a
13 business.

14 So, if they failed the urine test, what
15 happens? The money goes off to a local orphanage.

16 So, we then, also, in the data I'm going to
17 show you, we used the six-month results where we measured
18 the impact on -- measured the success of those who signed
19 up for the account, those who don't, as well as a control
20 group.

21 We also, very importantly, will go back after
22 12 months. And from a science perspective, from a social
23 science perspective, the 12-month results really are the
24 much better results to think about. Why? Because the
25 six-month results, there's incentives to cheat. There

1 was no surprise factor because it was pre-announced, they
2 knew we were coming in six months to do this, whereas the
3 12-month results, there was no money on the line at all.
4 Now, we're just seeing whether this continued to succeed
5 in getting people to stop smoking.

6 Here's a little picture of the urine test.
7 Well, not the urine part, just the test part.

8 ( .)

9 MR. KARLAN: There was an alternative treatment
10 that we gave people. It was -- by many, you know, it's
11 hard to say what the leading alternative would be, but we
12 wanted to do another treatment that would have really
13 high take-up rates. And there's also a policy that we
14 see implemented in many places. So, in Canada, it is
15 public -- it's law that you have to have these nasty
16 photos on the outside of your cigarettes, you know, the
17 package as you buy it.

18 And so, we gave out these cue cards that had --
19 these are the pleasant photos, by the way. The other
20 ones were really much uglier. And they were basically
21 intended to be a cue card that people put in their wallet
22 or in their house somewhere that basically reminds them
23 of the potential negative consequences of smoking. This
24 is meant to mimic the closest we -- you know, kind of a
25 popular public policy.

1 So, here's the project flow. We start off in
2 the project with a baseline survey. We basically have
3 these bank officers literally just walking through the
4 streets is the exact process. They would walk through
5 the streets to markets, knock on doors of business, and
6 go up to people who were smoking, or even if they were
7 not and just ask them if they were smoking. So, their
8 basic filter was, do you smoke every day? If yes, then
9 they went and filled out a little five to ten-minute
10 survey.

11 And then in the first two phases of the study,
12 we -- each survey form on the back of it had a sticker
13 assigning people to one of different -- either the CARES
14 treatment group or the CUES cards or control in which
15 nothing more was done.

16 In the third phase where most of the data comes
17 from, it was randomized through a -- not exactly
18 technically random, but effectively random process by
19 calculating the residual of the day, month, year of their
20 birthdate and dividing by three, and using that to
21 assign. The reason for the change is because we were
22 getting afraid that there was cheating going on in the
23 first method.

 So, then they're offered the product. Iffirstnr3 TDmlhtt

1 had two different CARES products that we were offering,
2 one without and one with deposit collection. Only seven
3 people took up the product without the deposit
4 collection. It was clear that we were not going to have
5 statistical power to separately test out the importance
6 of the deposit collection, so we got rid of it in the
7 full scale-up and only did it with the deposit
8 collection.

9 So, this now remains kind of a key question for
10 us. It's one thing to have low take-up; it's another
11 thing to have low effectiveness. It would still be very
12 interesting to note what the effectiveness is because you
13 can imagine with a different technology, for instance,
14 cell phone banking, that you might not need the deposit
15 collector, but that's something that remains for us to
16 have to test in a future wave. Then we do the follow-up
17 visit six months or 12 months into it.

1 statistical analyses we'll show you, we will be
2 controlling for the phase to take this into account. In
3 the first phase, we really were just testing the product
4 concept and the procedures for doing the randomization.
So, it was 45, 45 and then testing in 0 TD(2)Tj5.1 -yemlbnto accok5.in

controlling for 45, 45 and then testing in 0 TD(2)Tj5.1 -yemlbnto accok5.in

1 was even higher, above \$20, whereas the average for those
2 who forfeited was much lower, thank God.

3 And then the proportion of clients who missed
4 three deposits -- if you missed three deposits, then the
5 deposit collector stopped coming. It doesn't make any
6 sense any more. And that was only 14 percent. So, for
7 the most part, they -- just tracking usage, it was clear
8 that it was being used for the most part.

9 Baseline measures. So, this is going to show
10 you a little bit about why we got nervous about the
11 randomization routine that we were using or lack thereof
12 in the phase one and two. And oddly enough, it's the
13 CUES treatment that seems to be mostly off-balance, not
14 the CARES. So, as you can see on the bottom row, for
15 instance, wanting to stop sometime in your life, the CUES
16 treatment is significantly lower than the control, 69
17 percent versus 75 percent.

18 So, more interestingly, we do find on who's
19 taking up kind of what you would like to see in the
20 simple correlation results here. So, you know, those who
21 take up are more likely to want to stop smoking than
22 those who do not take up. That's good. That means
23 they're understanding.

24 Flip to the next page, want to stop smoking
25 now, 29 percent in the CARES group want to stop now

1 whereas only 16 percent of those who do not take up want

1 the different columns what we have are the different
2 assumptions about how we deal with the drop-out, the
3 people who we fail to test. And the results, as you can
4 see, are fairly robust to whatever assumption we put in.

5 So, you know, what we find is a 3.3 percentage
6 point impact on the -- keep in mind, this is on the
7 intend to treat analysis. So, we have one out of nine
8 taking up. Eleven percent of the people who were offered
9 took up. So, what we notice here is that the CARES
10 treatment is actually not statistically better than the
11 CUES on the intent to treat analysis. Why is this?
12 It's, hopefully, fairly straightforward. We have 100
13 percent take-up in the CUES treatment, but only 11
14 percent in the CARES. So, the intend to treat is
15 diluting the effectiveness of the CARES radically in that
16 sense.

17 When we look at the treatment on the treated,
18 as you can see, now the CARES treatment blows up to nine
19 X roughly and we have a 30 percentage point improvement
20 in the likelihood that someone stops smoking relative to
21 the control group, whereas the CUES card stays where it
22 was because there was perfect take-up. So, it's not
23 different. And, now, we have a statistically significant
24 difference between the CARES and the CUES, which is kind
25 of the best analysis to do on an apples to apples basis.

1

Now, like I mentioned earlier, this is really

1 of product, this question of sophisticated versus naive,
2 I think, is very, very important.

3 The one thing that's important to note is that
4 the deposit collection and the process of having a bank
5 officer come, in itself, is an element of a commitment
6 contract. So, if this works strictly because of the
7 deposit collection, it's not a criticism of this being a
8 valid test of time inconsistent preferences. What it
9 means is there's two things that happened in terms of
10 raising the price of smoking. There's financial and
11 there's social shame. And the deposit collector could be
12 working because of the social shame of a bank officer
13 coming to your door and saying, have you stopped this
14 week, are you still smoking, give me your money.

15 And even if it's not about the money, there's a
16 social shame factor and simply opting into a system, into
17 a process that you're going to have someone come to your
18 door and shame you, that's, again, still evidence of time
19 inconsistency. It's evidence that you don't need the
20 financial contract to do it, you just need social
21 pressure. But that there's still -- you're still doing
22 this same exact behavior, still raising the future price
23 of cigarettes. You're doing it either through social
24 shame or through finances. We can't separate out those
25 two stories in the study that we did.

1 That's all. Thank you.

2 (A .)

3 MR. LIST: Thanks, Dean, that was very
4 interesting. Now, anything pressing?

5 (.)

6 MR. LIST: Great. We're going to jump to a
7 quick discussion from Robert Letzler who is a recent grad
8 doing behavioral economics from Berkeley and now he works
9 here at FTC. And I want to publicly thank Robert because
10 he screened all of these papers with me and he was part
11 of the process as well. So, thanks a lot, Robert, for
12 your help.

13 MR. LETZLER: Thank you. So, the first thing I
14 should observe is I was supposed to have a tag team
15 partner for this discussion, but he couldn't make it.
16 So, I may wrestle with these ideas all by myself, which
17 leads to the next disclaimer that the opinions expressed
18 here are just my own.

19 So, I think actually our speakers have gone
through my 17

1 should go to the gym. Tomorrow, I eat potato chips and I
2 veg out on the couch and the day after tomorrow I said,
3 really, I should have eaten the broccoli and I should
4 have gone to the gym.

5 So, as Dean Karlan has pointed out, if you know
6 that you have this problem, you're going to seek
7 commitment devices. So, these two papers tested two of
8 the plethora of testable implications of this model. So,
9 Karlan's paper has, I think, very interesting good
10 evidence that some people are sophisticated, they know
11 they have self-control problems, and so, they demand
12 commitment devices and successfully use them.

13 The next thing I would like to point out is for
14 neoclassical curmudgeons, and I can go into that mode
15 once in a while. They can kind of explain away some of
16 the other famous commitment device papers. There is --
17 famously, Benartzi and Thaler have a save more tomorrow
18 paper. People commit to saving more money. This, for a
19 lot of people, is actually committing to a good thing.
20 Then, again, neoclassical out, I can quit any time. So,
21 it's not really a -- it's a fairly weak commitment.

22 Ariely and Wertenbroch have something stronger.
23 They say, students in my class, do you want to opt into
24 deadlines. If you do, if you sign up for a deadline, we
25 professors will enforce them and grade you down if you

1 miss them. But, again, if I have friends who want me to
2 do stuff and give me these social obligations, I need to
3 beg off, it may be very handy to have these deadlines
4 around. I can't do it this weekend, I've got to study.

5 On the other hand, CARES participants are
6 volunteering to be fined. My sense is if I were teaching
7 undergraduates, I would have an exam question, please
8 explain to me why our theories say you would never do
9 that. If we have actors with no self-control problems,
10 participation may be a dominated strategy if either -- if
11 you can imagine any scenario in which it would be
12 rational to delay quitting or if there's any scenario in
13 which the test could err.

14 Maybe a neoclassical person could say, I
15 anticipate some future guilt if I forget to pay -- I'm
16 sorry, if I forget to quit smoking, then second-hand --
17 people will be breathing my second-hand smoke. If I am
18 giving this contribution to the orphanage, I'll feel
19 better. But it's not that satisfying.

20 On Stephan's paper, as he says, there's lot of
21 evidence as present-biased in the lab. There's plenty of
22 stuff out there that looks and feels like present-biased.
23 Finally, we have this and a few other papers that really
24 have strong measures of lab tests for cash and actual
25 field behavior linked to each other, which is a great

1 thing.

2 One sort of warning to future authors is we,
3 basically, are identifying everything off of two sets of
4 questions that are measuring time inconsistency. For
5 anyone doing this again, please nail that down better.

6 James Hilger's paper, the design and the
7 analysis is convincing and very thorough. My personal
8 bent is I'd like to see this better tied to a big
9 intellectual project. So, what do we learn about how
10 consumers make decisions?

11 One of the stories, I think James actually
12 didn't get to talk about was, for high-priced, high-
13 quality wines, there's no impact of labeling. We're only
14 seeing it on the low-priced wines. So, are the people
15 who are buying those high-priced wines not responding?

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1 sophisticated, the kind of firm that could hire Peter
2 Crampton or Hal Varian or someone like that to figure out
3 how they should price, they seem to be committing up-
4 front buy enough and we'll give you free shipping and
5 handling. Sign up to be a loyal customer, and we'll give
6 you free shipping and handling.

7 It also is a pressure -- if I have this fairly
8 fixed sub-additive price of shipping and handling, to
9 either buy nothing or to buy a lot.

1 A E T E T E E : E C I C I F A T

2 MR. SHAPIRO: If you could please take your
3 seats, we'd like to start the next session now, please.

4 Good afternoon. Hi, it's me again. I'm just
5 moderating or chairing this session. The title is
6 economics of antitrust, which means we couldn't quite see
7 how the papers fit together very well, but they're all
8 really good. So, we have, again, three programs. You'll
9 see on your program.

10 Our first speaker, Michael Waldman, title of
11 paper, Why Tie a Product Consumers Don't Use?
12 Explanations-Efficiency, Price Discrimination and
13 Exclusion. Michael? Pat DeGraba is going to be the
14 discussant for this.

15 MR. WALDMAN: Thanks, Carl. So, this paper is
16 co-authored with Dennis Carlton and Joshua Gans. So,
17 this paper is kind of the last paper that Dennis and I,
18 and this one with Joshua, have written as a kind of
19 series of papers on time behavior. Most of the previous
20 analyses -- what we're doing in this paper is trying to
21 put forth a new explanation for why firms might tie. And
22 previous explanations or previous models have typically
23 focused on one of three arguments, either efficiency,
24 price discrimination or exclusionary rationales.

25 And our argument is a little bit different,

1 which is we have a profit-shifting rationale. The basic
2 idea is suppose you have a monopolistic that ties and the
3 tie itself has some efficiency property to it. What that
4 means is if the consumer just buys the monopolist's
5 primary and complementary goods, the consumer gets a
6 higher gross benefit from consuming the tied good than
7 from consuming individual goods.

8 And our basic argument is, now add a potential
9 alternative producer of the complementary good who has a
10 superior alternative complementary good by tying, even if
11 the primary -- even if the monopolist complementary good
12 is not going to be used, it serves as an option for the
13 consumer and it reduces the consumer's willingness to pay
14 for the alternative producer's complementary good, and in
15 that way, can shift profits from the alternative producer
16 to the monopolist. That's our basic story. I guess I
17 sort of already went through that slide.

18 So, let me go through an example just so you
19 can see it in a little bit more of a concrete fashion.
20 Suppose you have Microsoft, which is a monopolist of
21 Windows and a marginal cost, just to keep it nice and
22 simple of zero for Windows, and there's a complementary
23 good and the complementary good is Media Player. So,
24 Microsoft can produce the Media Player and there's a
25 rival that produces QuickTime and the marginal cost of

1 have that assumption all the time. We'll allow this
2 surplus sharing to be kind of anywhere between zero and
3 one.

4 AUDIENCE MEMBER: (Off microphone) So, I guess
5 the thing I really don't understand is if they're paying
6 20 and buying Windows and Media Player and they're buying
7 QuickTime as well --

8 MR. WALDMAN: That's right.

9 AUDIENCE MEMBER: (Off microphone) -- why are
10 they (inaudible) -- do they get the extra five surplus
11 (inaudible) Media Player for not using it?

12 MR. WALDMAN: They're not getting any -- the
13 consumer's not getting any additional surplus for Media
14 Player. It's a question of how much is the consumer
15 willing to pay for QuickTime.

16 AUDIENCE MEMBER: (Off microphone) (Inaudible).

17 MR. WALDMAN: So, it's only willing -- so, if
18 I'm owning a good, which if I'm a consumer, I get \$20
19 worth of gross benefit, and if I buy this other good, I
20 get \$25 worth of gross benefit, I'm only willing to pay
21 \$5 for the good. If I'm owning a good -- if I'm owning a
22 set of goods which -- or potentially owning a set of
23 goods which only give me 15, now I'm willing to pay \$10
24 for the good. So, there's this extra functionality which
25 actually winds up not being used in equilibrium, but it

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1 paper, but anyway, I'll go through the rest of the
2 presentation anyway.

3 (.) .)

4 MR. WALDMAN: So, this paper captures and
5 extends the logic of that example. We have a monopolist
6 of a primary product, a complementary good that can be
7 produced by the monopolist and a rival. Consumers only
8 have valuations for systems, just like in the example we
9 just did, and ties are reversible.

10 I'll go through or the paper goes through three
11 different analyses. It goes through an identical
12 consumer analysis along the lines of the example we just
13 did. That's a simple case of heterogeneous consumers and
14 also has our endogenous R&D choice by the monopolist. In
15 each case, what we show is that you can get tying when,
16 at the end of the day, the tied product, the
17 complementary good that's being added to the primary
18 product, is not used in equilibrium. So, that's a social
19 welfare loss if there's some cost of producing this
20 complementary good. And we also have a second social
21 welfare loss which we talk about in the third model,
22 which is this R&D cost of producing this complementary
23 good in the first place.

24 So, the talk is going to be, as much as I can
25 get through, relationship to the previous literature,

1 model analysis, R&D distortions, just a brief discussion
2 on antitrust, since this is labeled antitrust, and a
3 conclusion.

4 So, if you look at most of the previous models,
5 and I've listed a few of them, Whinston, Choi and
6 Stefanadis, an earlier paper I did with Dennis, and
7 Nalebuff where the tying is used to disadvantage rivals,
8 mostly the tying is used either to cause exit or block
9 entry.

10 And what we're doing is quite different than
11 that. So, our tying is used to disadvantage rival,
12 reduce the profit of a rival, but the goal is not to stop
13 the rival from entering the market or cause the rival to
14 exit the market, rather the goal is to take some of the
15 rival's profits and shift it over to the primary good
16 producer.

17 Now, a famous result or an important result in
18 the tying literature is a result that goes back to
19 Whinston which shows if the monopolist primary good is
20 essential, then there's no return to tying. What do
21 I mean by essential? Essential means that the monopolist
22 -- that the monopolist's primary product is used -- if
23 you want to use the complementary good, you have to get
24 the monopolist primary good. And in Whinston's models,
25 if that was the case, then there was never a return to

1 tying.

2 What we show, in this alternative model, is
3 that you can get a return to tying even if you have this
4 essential element. Our model's a little bit different.
5 A, we assume that ties are irreversible -- I'm sorry,
6 Whinston assumed ties are irreversible and no efficiency
7 associated with the tie. What we're showing is that if
8 you remove those two assumptions, irreversible means if I
9 tie the product, I can't add someone else's product to
10 the tied system. And, so, especially if I'm talking
11 about Microsoft, that's not that realistic. So, we more
12 realistically assume reversibility and we also assume
13 this possibility for efficiency associated with the tie
14 and when you allow for those two things, then Whinston's
15 essential result winds up going away.

16 There's also a couple of papers that look at
17 independent products where the role of the tie is to
18 reduce competition in one of the markets, Carbajo, de
19 Meza and Seidman. Our paper is a little different than
20 that because we're allowing -- we have complementary
21 goods and the role of the tie is quite different than
22 what's going on in those two previous papers.

23 Actually, our paper is closest to a paper by
24 Farrell and Katz, which was in the Journal of Industrial
25 Economics in 2000. What they basically show is that

1 there's various behaviors that a firm might take on to
2 create a price squeeze for the completely good producers,
3 integration, R&D, exclusionary deals. What we're showing
4 is that basically their argument also applies to tying if
5 you allow for reversible ties and you allow for these
6 efficiencies associated with the tie.

7 So, here's the model. I'll go through it very
8 quickly. We have a monopolist and a single-alternative
9 producer in a one-period setting. There's a constant
10 marginal cost for the monopolist for the primary good of
11 CP. The complementary good, both for the monopolist and
12 the alternative producer, there's a constant marginal
13 cost of CC and the alternative producer's complementary
14 good is superior.

15 Goods are only consumed in systems. Ties are
16 reversible and tying is weakly efficient. So, basically,
17 if the consumers consume the alternative -- the
18 monopolist tied primary and complementary goods, as
19 opposed to the alternative producer's complementary good,
20 there's at least -- it's weakly efficient to have them
21 tied. And in this first model, it's identical consumers.

22 Here are the gross benefits, VM if an
23 individual purchases the monopolist's products and
24 consumes the monopolist's products purchased separately.
25 The consumer gets an extra delta if the product is tied.

1 The consumer gets VA if the consumer has the monopolist's
2 primary good and the alternative producer's complementary
3 good, and it's then the max of VM plus delta and VA if
4 the consumer buys the monopolist tied product and then
5 adds the alternative producer's complementary good.

6 The timing of the game is the monopolist
7 decides whether or not to tie. Oh, just one quick aside,
8 the current version of the paper is a little bit of a
9 mistake. We claim that it generalizes the mixed
10 bundling. That's not actually true and we're in the
11 process of rewriting the paper to fix that up.

12 Firms choose prices and then consumers
13 make their purchase decisions. We look at a sub-gain
14 perfect Nash equilibria, and as I was saying earlier,
15 this is a -- it's well-known or at least people who work
16 in this area know that this is a gain where there's
17 frequently multiple equilibrium and that's true of this
18 gain, and we're going to resolve that multiple equilibria
19 problem by assuming that -- we're going to assume that
20 the alternative producer's product is superior, the
21 monopolist gets -- I'm sorry, the alternative producer
22 gets λ of its superior product and the monopolist
23 gets one minus λ .

24 If I have time, I'll actually talk a little bit
25 about what happens when you move away from that strong

1 assumption and allow lambda to vary whether or not the
2 monopolist ties or not.

3 So, parameter restrictions, we assume that it's
4 efficient for the monopolist to release its products,
5 which means $VM > CP + CC$, Δ is greater
6 than zero, greater or equal to zero. That just means
7 there's an efficiency -- weakly efficiency associated
8 with tying. $VA > VM$ means the alternative
9 producer's product is superior.

10 So, the first result is to basically generalize
11 Whinston's result, which says, if there's no efficiency
12 associated with the tie, if $\Delta = 0$, then
13 there's no reason to tie in this world. So, Whinston's
14 result goes generalize, even with reversible ties in our
15 model, as long as there's no efficiency extra
16 functionality associated with the tie.

17 But if we allow this extra functionality, Δ
18 greater than zero, then you get the following set of
19 parameter values translating to different types of
20 behavior, and you can take those five regions of the
21 parameter space and translate them into efficient and
22 inefficient behavior.

23 So, parameter condition one translates into
24 efficient tying; three and five on the previous slide
25 translates into efficient sales of individual products by

1 heterogeneous consumers just showing if you introduce a
2 small number of -- a second group who have different
3 preference characteristics, you can still get similar
4 results.

5 Then what we do -- in terms of thinking about
6 this as Microsoft, you might say, well, gee, I'm not sure
7 that the Microsoft's marginal cost for having a --
8 putting its goods onto Windows is really very high, and
9 so, that might be a social welfare loss that I really
10 don't care about it. It might be second order.

11 So, we spend a few pages talking about, well,
12 suppose we add R&D decisions into the paper, and so, in
13 particular, we allow this delta, the extra functionality
14 to be either small or large where it's a function of the
15 amount of investment that Microsoft makes into the R&D
16 process for producing this complimentary good. And then
17 we stick with the same parameter range from the previous
18 analysis where you got this inefficient time where the
19 good wasn't actually used but still purchased.

20 And to make a long story short, you can go
21 through that analysis and what you find is you get a
22 second social welfare distortion. What's the second
23 social welfare distortion, the second social welfare
24 distortion is that Microsoft winds up investing in this
25 R&D even though, in this part of the parameter space, the

1 consumers never actually use Microsoft's products. So,
2 Microsoft frequently ties and the consumers aren't using
3 the product and, yet, it's -- the reason it's tying is
4 because it's a way of causing, an expected value sense,
5 more of the profits to be shifted from the rival to the
6 monopolist.

7 And then we also do -- this is not in the
8 paper. We also do a second analysis where the
9 alternative producer has an R&D decision and what you
10 find there is that this type of behavior can cause a
distortion s3n s3

1 So, it would be very hard for the Courts to really figure
2 out that this is really what's going on as opposed to
3 it's just a standard efficiency argument where, in fact,
4 Microsoft just -- or the monopolist just wound up not
5 producing a good enough product.

6 Conclusion. So, what we've done in this paper
7 is provided a new explanation for tying, which is
8 basically a profit or a rent-shifting explanation. And
9 in terms of kind of focusing what -- more specifically
10 what have we done, we realistically allow time to be
11 reversible which is, I think, an advancement over the
12 previous literature. We show why a firm might tie even
13 if the consumer's product is not used in equilibrium and
14 that seems consistent or at least roughly consistent with
15 some of the things Microsoft tends to do.

16 We show that Whinston's result concerning the
17 essential nature of the product be important as to
18 whether or not you see tying is not robust to this. And,
19 finally, from an antitrust perspective, what we would say
20 is we think that in this particular theory for harmful
21 tying, one should be very careful in terms of using this
22 as a basis for antitrust intervention just because it
23 only works when there's this efficiency. So, it would be
24 very hard for the courts to pull out that this is exactly
25 what's going on as opposed to that Microsoft or the firm

1 was trying to do something efficient and that wasn't
2 quite as successful in terms of the quality of the
3 product that was produced.

4 MR. DeGRABA: So, it's an idea that I like, but
5 it's a model that I think could be streamlined and could
6 have avoided most of the conversation here about multiple
7 equilibria. In fact, this paper -- 90 percent of this
8 paper, actually, isn't about tying at all. It's more
9 about, sort of, the Cournot Complements problem and the
10 idea is simply that if one firm has a primary good and a
11 competitor is offering a complementary good, a really
12 high price for the complementary good means the
13 monopolist can't sell the primary good at a very high
14 price or sell very many of them.

15 Anything you can do to get the complementary
16 good provider to lower the price means he can either sell
17 more units or raise the price or typically both of the
18 primary good. So, in this paper, if the primary good
19 supplier also offers another complementary good, even if
20 it's inferior, it provides some competition for the good
21 complementary good. It lowers the price of the good
22 complementary good and increases the price that can be
23 charged for the primary good.

24 In this particular paper, one of the ways to
25 make the primary good -- to lower the price of the

1 complimentary good is to simply tie a product for which
2 consumers have some utility for the tying. That makes
3 the bundle sort of more beneficial, it lowers the price
4 that the superior complimentary good can charge and it
5 raises the profits of the firm.

6 What I want to talk about probably will bore
7 most people, but probably not Mike. And I want to argue
8 or I want to at least suggest, I spent a week thinking
9 about the paper, and I want to simply say that if you --
10 instead of having a model where all the consumers value
11 the primary bundle the same, if you have some price
12 sensitivity to that, you can get rid of the multiple
13 equilibria problem. You can get a unique equilibrium and
14 a unique price and you can actually get more results out
15 of that model than you can out of what's in your paper.

16 So, in the -- I have the new model here, the
17 model I'm going to propose. Instead of everybody valuing
the complementary bundle at some constant amount, we'r17

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1 dominant strategy for the monopolist -- and, so, the
2 model is then everybody sets prices and customers buy
3 what's best for them. I'm going to argue that the
4 dominant strategy for the monopolist is to set his
5 complementary good at zero and that the alternative
6 complementary good provider would never set the price of
7 his good more than E above the price of the monopolist
8 complementary good if there's no tying and no more than E
9 minus delta if there is tying.

10 The graph of the -- the incentives to tie are
11 easily shown in this graph. If there's no tying,
12 alternate -- the complementary good producer simply
13 charges E , the extra value of his good. The monopolist
14 sets the price of zero for his complementary good, and
15 then he's basically faced with a residual demand curve,
16 which is just a demand for the monopoly good.

17 So, the three curves up here, the green one,
18 which is the lowest one, is just a demand for the
19 monopolist bundle. The red one on top is the demand for
20 the bundle with the alternate -- with the good -- extra
21 good in it.

22 In the no-tying equilibrium, the monopolist
23 sets the monopoly price for his own bundle and the
24 alternate firm captures E for all the units that he
25 sells. When the tying occurs, what happens is that the

1 value that the alternate producer can charge is now his
2 extra value minus the new delta that got introduced. So,
3 he has to lower the price of his good by delta. That
4 shifts the demand curve for the monopoly good up to W
5 plus delta, which is the purple line. That new higher
6 demand curve allows the monopolist to raise his price.
7 So, in equilibrium you have -- the tying prices are E
8 minus delta and W plus delta over two.

9 Why is that interesting? Well, in this
10 particular case, if you notice the price of the tying
11 good went down by more than the price of the primary good
12 went up. So, this says that if you have this efficiency
13 going on, that tying will actually lower the price to
14 consumers of the overall bundle -- that's a result that's
15 not in the paper.

16 There's a second equilibrium that I'm not going
17 to go through, but if E is big enough, then it turns out
18 that the price of the ultimate complementary good isn't
19 really constrained by the monopolist complementary good,
20 that he'd actually rather charge a price lower than E in
21 equilibrium. And in that case, you'll find that tying
22 won't do anything at all.

23 And there's one other result and then I'll
24 finish, which is -- which I'm only sort of convinced of
25 because I haven't actually done the math, which is that

1 in equilibrium, when there's no tying and there's
2 positive marginal cost, the monopolist still sets his
3 complementary good price at zero. So, if you were to do
4 something like tell Microsoft not to bundle, say, Windows
5 and some media player, for instance -- and by the way,
6 I'm invoking the disclaimer for FTC employees at this
7 point -- that this model predicts that in equilibrium,
8 Microsoft will give away Windows Media Player and not
9 charge a positive price for it.

10 The final thing I want to say is that this
11 model had sort of valuations differing for the monopolist
12 good and everybody viewed the alternate good with the
13 same valuation. If you reverse those assumptions, the
14 model becomes much more complicated, but also, I think,
15 much more interesting. It's something that ought to be
16 worked on. Thanks.

17 MR. SHAPIRO: All right. Let's move right
18 along. So, as you can see, our next speaker is Minjae
19 Song, Sleeping with the Enemy: Inter-firm Product
20 Combinations.

21 MR. SONG: This paper is with Claudio Lucarelli
22 and Sean Nicholson. Both of them are at Cornell. The
23 paper is still preliminary.

24 So, this paper is about the product
25 combination, but inter-firm product combination. So,

1 2,500 to 2,000. And the first example is the stand-alone
2 -- the regimen by Sanofi. This one is another cocktail
3 made of the drug by Sanofi and then Roche.

4 So, we treat each -- the recipe as a product.
5 And we have the market share data on each regimen in the
6 market.

7 So, the question we have here is whether these
8 cocktails increase the firm's profits, and if it does,
9 then how much it would increase the profit. And whether
10 the cocktails make drug prices higher or lower compared
11 to the market without a cocktail.

12 We are also interested in consumer welfare.
13 So, we ask if consumers are better off or worse off with
14 this cocktail. So, if you take out this cocktail,
15 then -- I mean, if you provide this cocktail, there's
16 more variety the wider set of the choice, so a consumer
17 may get better off with a cocktail, but there's also a
18 pricing issue. So, depending on how the price changes,
19 with a cocktail, the consumer welfare may get affected.

20 So, our approach is kind of an empirical
21 approach since the -- kind of the cocktail structure in
22 the market is quite complicated, we look at data and then
23 we estimate regimen level demand model using the discreet
24 choice model. Then we assume that market is Bertrand
25 Nash equilibrium. So, the firms set drug prices and the

1 price that we observe in the market is in Bertrand Nash
2 equilibrium. So, we can recover the marginal cost from
3 the estimated demand.

4 Then given the demand estimates and the
5 marginal costs, we did two counterfactual exercises. The
6 first one is we take one cocktail out of the market one
7 at a time and then we recompute the equilibrium price and
8 then see how the profits and consumer welfare change.

9 The second counterfactual -- in practice, in
10 the market, the firms can only set one price per drug.
11 But in the counterfactual, we allow a firm to set two
12 prices. So, one price for a stand-alone regimen and the
13 other price for the drug used in the cocktail regimens.
14 It's kind of an interesting exercise because in the AIDS
15 treatment segment, there's a company called Abbott and
16 they actually have two drugs. They used to have only one
17 drug and that drug was used in a cocktail, combined with
18 its rival company. Then they were about to launch a new
19 drug in the market, and to secure the market share for
20 this new drug, they increased the price of their existing
21 drug by about five times.

22 So, there was an article in the Wall Street
23 Journal, and I think FTC is kind of looking at that case
24 this year.

25 So, we kind of tried to mimic that case,

1 solo regimen, and the second source of profit is this
2 cocktail regimen. And assuming the Bertrand Nash, you
3 can solve this profit maximization.

4 The first little condition is slightly
5 different from kind of the standard one that we know
6 because of there's two abstract (inaudible) here because
7 you not only care about the elasticity, the effect of the
8 share from the price change of P_1 . It's only elasticity
9 and cross-elasticity. But you also care about the effect
10 on share through the price of the third regimen, which is
11 the function of the two prices here.

12 So, the stand-alone regimen is just how much
13 dosage you use times the price per milligram. But the
14 price for the cocktail regimen is the function of your
15 price and your rival's -- the price. And when you set
16 the price one, you have to look at the effects through
17 the regimen price -- the price of regimen one and the
18 price of regimen three.

19 So, this is kind of the simplest setting that
20 we can think of. In the paper, we did some numerical
21 simulations, given this very simple duopoly setting. We
22 do the kind of two counterfactual data. I'm going to
23 show in this simplest setting and then we kind of see --
24 we analyze what happens. It's not really the same -- we
25 don't get the same jumps in the data because of the more

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1 exit. But we don't observe any major exit here.

2 So, the first stage statistic of the
3 (inaudible) IB (inaudible) 16. So, the second type of IB
4 we tried is we used the other regimens' prices in T minus
5 one. So, the assumption is the prices also correlated
6 over time, but demand shock is not. So, this is kind of
7 our identifying assumption.

8 We're concerned about the weak instruments, but
9 (inaudible) is over 60 on the first stage. And this is
10 our (inaudible) and IB and (inaudible). What is
11 interesting is even without any instruments, we have
12 negative price coefficients. So, it's actually
13 physicians who make this decision and they are about
14 price. And the first IB doesn't really change much of
15 the coefficients. But the second one, it decreases the
16 price coefficient a lot. Some of the signs are not
17 really interesting. So, the time to progression should
18 have a positive coefficient, but we have a negative.

19 So, the only -- I mean, in all specification,
20 the only coefficient that makes sense is response rate.
21 But what we think is the -- is how to separate the three
22 efficacy from each other. So, when you kind of think of
23 the utility from the drug, you have to think about it as
24 a combination of this efficacy.

25 And side effects do not really come out in a

1 significant way mainly because physicians also control
2 the side effects by giving like a drug for the diarrhea
3 and a drug for the vomiting. We think that could be the
4 way.

5 So, let me -- in my remaining four minutes --
6 three minutes, okay. Let me show you my counterfactual.
7 So, the first counterfactual, we take out one regimen at
8 a time. There are six cocktails in the market. So, each

1 This is the profit. So, the profit shows that
2 for every case, the firms get worse off without a
3 cocktail, without a cocktail. So, some of the profit
4 changes are very, very significant. For example, in
5 here, Imclone's profit level without a cocktail is about
6 21 percent of its current -- the profit. The reason is
7 that Imclone's cocktail has larger market share than its
8 stand-alone.

9 You look unhappy, so I will finish. So,
10 Imclone's -- the cocktail's market share is much higher
11 than its stand-alone cocktail. Another example is
12 Genentech. The profit goes down to the 25 percent level
13 of the current level because Genentech doesn't have any
14 solo regimens, stand-alone regimens. All of Genentech's
15 products are the cocktail regimens. So, they get hurt a
16 lot by the -- without the cocktail.

17 Consumer welfare. So, consumers care about two
18 things. One is the variety and second is the price. So,
19 when you take out cocktail, the welfare goes down because
20 there's one less product on the market. But in two
21 cases, they're actually better off without a cocktail.
22 Why? Because without those cocktails, the price of other
23 drugs goes down so that they get more benefit from lower
24 price than extra products in the market. So, we have
25 kind of an interesting result.

1 questions, especially to study the pricing strategies
2 when firms use -- may have inter-firm product
3 combinations.

4 So, let's just first give a brief summary about
5 the main finding of the paper. So, this paper tried to
6 study the pricing strategies when firms use inter-product
7 combinations. And the strategy they use is try to
8 estimate the amount of systems at the regimen level. And
9 then they tried to recover the cost parameters from the
10 Nash equilibrium conditions. After that, they will be
11 able to perform counterfactuals to evaluate the impact of
12 product bundling.

13 So, here are some of the comments. So, first
14 of all, it is very important to get the demand estimates
15 right. Because the starting point of your analysis, you
16 have to back out the marginal cost and the counterfactual
17 analysis.

18 However, right now, the paper uses (inaudible)
19 logic demand functions by basically transforming the
20 market shares and then it becomes a linear function so
21 you can use the IB approach to estimate the price
22 coefficient. The main problem with IB (inaudible) demand
23 function is that the estimates of the demand elasticity
24 are completely driven by the market share of the regimens
25 and this is a well-recognized problem using the simple IB

1 (inaudible) demand functions. So, you could try to, for
2 example, adding random coefficients and also especially
3 the additional consumer characteristics and also the
4 interaction in terms of consumer characteristics with the
5 (inaudible) observed (inaudible) observed the random
6 coefficients, and that's shown in the literature to be
7 very important to get the demand elasticity right.

8 Additional robust check, the market structure
9 changes a lot during the sample period. In the beginning
10 of your period, there is one drug that has almost like a
11 90 percent of market share, it's like a monopoly. And at
12 the end of your sample period, for these particular
13 regimens, the market share is only something like 10
14 percent and you have 12 regimen combinations. So, I
15 would say that maybe try to use the later periods,
16 probably you don't have enough observations, I'm not
17 sure, to see whether the estimate still holds or whether
18 you have some changes in your results.

19 Another recommendation is to do reported
20 estimates of the delta coefficient that you get because
21 this is going to be important. Depending on the value of
22 delta so that will affect the mixing strategies. Also,
23 it would be interesting to know what is the estimated
24 delta coefficients and how that relates to your other
25 simulation results.

1 Additional comments, so the simulation results
2 is still fairly restrictive of function of firms. I'm
3 just quite curious to know whether your simulation
4 results hold for a more general demand function or it's
5 something like a -- the result of treatment by the
6 peculiar logic demand functions.

7 Another important thing is the law of
8 advertising when you have product bundling. This is
9 important because your simulation counterfactuals show
10 that when firms choose different prices for a solo
11 regimen and bundled regimen, then you have dramatically
12 different prices. So, you could think about it, if this
13 is indeed true, then this actually makes advertising even
14 more important. You could choose a same price for the
15 product, but you can adjust the demand by changing your
16 advertising intensities for a different regimen.

17 The differing data probably would be difficult
18 to get, but I think one way to do that would be to try to
19 get some sort of like direct-to-consumer advertising
20 data. This type of data, I think, is usually available
21 and you could get, for example, how much they spend on
22 the direct-to-consumer advertising and for different
23 regimens and to see whether that has any impact on demand
24 functions.

25 The last thing I want to say is about the

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1 entry accommodation or an entry deterrent story that's
2 going on here.

3 To summarize, I think this paper is really
4 interesting and I really enjoyed it.

5 MR. SHAPIRO: Thank you. Again, we could take
6 a couple questions. Yes, would you step to the
7 microphone, please, so you can be heard. Minjae, you
8 might want to come up here to respond.

9 AUDIENCE MEMBER: So, my question is whether we
10 should consider dosage to be endogenous at the firm
11 level. I would imagine -- this is out of my naive
12 knowledge of pharmaceutical -- is that if you take out a
13 cocktail bundle, the firm could re-choose their dosage so
14 that consumers can bundle themselves in their own kitchen
15 instead of --

16 MR. SONG: So, in this case, physicians are the
17 ones who make these cocktails. So, in the paper we take
18 the dosage as exogenous and a fixed amount. But in
19 practice, physicians actually try with a different
20 dosage. So, if this regimen doesn't work on some of
21 their patients, they may increase some of those. So, in
22 practice, actually endogenous, but then we can do another
23 kind of derivative. When the price changes, how does
24 that affect the physician's choice of the dosage. But
25 they should be within some boundary because they cannot

1 just change it from 1,000 milligrams to 2,000 milligrams.
2 It should be bounded. But, yeah, that can be potentially
3 (inaudible).

4 MR. SHAPIRO: (Inaudible).

5 AUDIENCE MEMBER: (Off microphone) (Inaudible).

6 MR. SONG: We are planning two more things.

7 So, we will get -- not me, but my co-authors will
8 probably get the physician level data because the market
9 share data was computed based on the physician level
10 data. So, if we get physician level data, then we may be
11 able to model the physician's choice, like, you know, the
12 way they use (inaudible) it's kind of matched between the
13 drug and the physician and there's some risk of
14 (inaudible) in this match. Then we can probably come up
15 with the richer model of the demand.

16 Right now, we have only the regimen level data,
17 so we can still kind of stretch our model to accommodate
18 those features, but -- yeah, uncertainty. Uncertainty,
19 yes. I would kind of think about that, you know, on how
20 to -- how we can do this with data.

21 And the second thing that we are going to do is
22 we have the clinical trial level data. That's kind of
23 not really related to your question, but to our
24 discussant's comment. So, we kind of tried to link the
25 decisions in the clinical trial phase to the -- what's

1 monitoring. If you're able to monitor other rivals in
2 the market, then collusion should be easier. Another
3 thing at least that some people agree on is that demand
4 information also matters. If you know what demand
5 schedule you're going to face, then collusion should be
6 easier to achieve. So, I'm going to take a look at
7 whether experimentally this is the case and I think that
8 -- I have the second motivation a theoretical motivation,
9 although in the back of my mind I think this is the main
10 motivation, which is the opposing predictions of two
11 well-known theories about cartel stability.

12 On the one hand, we all know that the
13 predictions of Green and Porter, who basically say --
14 this theory is known as a theory that predicts finite
15 price wars that are triggered by low demand for a finite
16 period of time. I think I already said that.

17 In other words, most people know this theory as
18 in which collusion is more stable during periods of high
19 demand. On the other hand, we have a theory by Rotemberg
20 and Saloner who basically predict that price wars should
21 be observed demand is high and collusion, as a
22 consequence, is more stable during periods of low demand.
23 So, of course, there are different assumptions in the
24 models and these assumptions are going to be informing me
25 of the experimental design. But I think studying these

1 two theories is really important because of the opposing
2 predictions that they have and, also, because as many
3 theories of dynamic gains, we have several equilibria.

4 And an interesting question, at least for me
5 and for some people is, how plausible are these
6 equilibria or are these predictions by these models, for
7 example, as opposed to other predictions that are also
8 equilibria.

9 So, the last motivation, as you see,
10 experiments to explore this question, and I think
11 experiments can be a useful tool, especially here because
12 we have multiplicity of equilibria. I want to see how
13 likely some predictions are versus others, and also
14 because collusion is an illegal matter here in the U.S.,
15 data's really difficult to get. So, that's my general
16 motivation.

17 So, let me talk about the general set of
18 assumptions that I have for the two theories. You can
19 obviously cast these two theories slightly differently,
20 but you can cast them in a basic set of assumptions and
21 they're going to differ on their assumption about the
22 nature of demand. So, we're going to assume that both
23 theories have homogeneous products, competition is
24 Cournot, firms are symmetric and they have constant
25 marginal costs. This is always (inaudible).

1 And the key thing here, the key difference
2 between the two models is that Rotemberg and Saloner,
3 although in their setup, demand is stochastic. They wake
4 up and they know what demand is going to be tomorrow.
5 So, some of the uncertainty is removed and that's why I
6 have in both letters that they have perfect information
7 on T plus one, although they don't know what they're
8 going to face T plus two.

9 The other thing that they assume is that firms
10 have perfect monitoring available to them. In other
11 words, they wake up with a profit and they also know what
12 other people chose as quantity.

13 Green and Porter, on the other hand, have a
14 much more uncertain environment in which there's
15 uncertainty about all future and past demand shocks and
16 the additional assumption they have is that there's
17 imperfect monitoring. In other words, you wake up with a
18 profit. You see an imperfect signal and you don't know
19 what other people chose in the market.

20 So, this is basically the difference between
21 the two models and this is -- these differences are going
22 to allow me to construct an experimental design.

23 So, very briefly, the reason why the Rotemberg
24 and Saloner prediction comes up is because since you know
25 tomorrow you're going to face a big demand shock, then

1 the incentive to collude, which is the left-hand side of
2 that equation, gets really big compared to what the
3 punishment you would get if you actually deviate.

4 So, when the demand shock is very low, then you
5 have the second equation where the inequality is reversed
6 and you actually have collusion -- you actually have --
7 the deviation doesn't pay off. Of course, there are
8 other equilibria. I'm going to compare the results that
9 I get with respect to other equilibria.

10 Very briefly, again, the tradition of Green and
11 Porter is one in which you have an imperfect signal of
12 what's going on in the market. In other words, you can't
13 see what other people are actually seeing as quantities.
14 So, you wake up with a low profit. This could either be
15 caused by a rival's defection or by low demand. You
16 really don't know.

17 But the equilibria is what I like to call the
18 mafia-like equilibrium where everyone is suspicious about
19 everyone else and there's this imperfect monitoring
20 device, which is price. And if this price falls below a
21 threshold level than everyone starts a price war, even
22 though no one deviated. And this is the kind of
equilibrium that they enter r you w eltj

16

1 low price. And the only way they can see a low price is
2 because of low demand shock. So, this is the main thing
3 -- the main prediction.

4 Now, something really important about Green and
5 Porter is it is known as a theory of finite price wars,
6 where you calibrate the N , that N star that you see
7 there, so that you just offset the incentives to deviate.
8 So, you just make firms indifferent from deviating today

1 This is a repeated game. The way I deal with
2 the infinitely repeated aspect of it is using a procedure
3 that experimentalists have used in the past, which is a
4 random (inaudible) rule, in this case, 20 percent
5 probability would simulate a discount factor of delta
6 equal to .75.

7 In the three treatments that I have, the first
8 and the third one that you see there are supposed to
9 resemble the assumptions of the two theories. So,
10 remember on the one stream we have Rotemberg and Saloner,
11 perfect demand information and perfect monitoring, and
12 Green and Porter is at the other extreme where you have
13 imperfect monitoring and imperfect demand information.

14 So, I separate one of the two effects by
15 considering a middle treatment where I have firms being
16 able to monitor what everyone else is doing, but they
17 don't know -- but there's uncertainty about the demand
18 schedule.

19 So, let me show you what subjects actually see
20 to give you a better feel for what the design looks like.
21 So, very briefly, subjects go through intensive training
22 and when they get to the part where they choose their
23 quantities, they see these matrices. The left-hand side
24 is displayed permanently to them. We use callers to tell
25 them to distinguish their pay-offs from the rival's pay-

1 offs and also medium, high and low demand schedules. The
2 probabilities are always displayed and this particular
3 decision screen is for people who anticipate what demand
4 schedule they're going to face. This would be the
5 Rotemberg and Saloner design.

6 After they make their decision, we show them
7 their profit by highlighting the entry in the cell that
8 corresponded to what they chose and the other party
9 chose. So, I notice that they have perfect monitoring
10 here.

11 The middle treatment where they have uncertain
12 demand information, they know that they're going to face
13 one of these three. They make a choice and after they
14 make the choice, we inform them of their pay-offs by
15 showing them this matrix and you can see that they can
16 also infer what the other person did. So, they have
17 imperfect demand information, but they have perfect
18 monitoring.

19 So, the key thing about our design is that in
20 the third treatment where they have imperfect monitoring
21 and imperfect demand information is that this would be
22 the resemblance of the Green and Porter paper, is they
23 wake up with a profit, but there is uncertainty about
24 what the other person did. In this particular case, the
25 subject chose to deviate. He woke up with a profit of

1250, but he really doesn't know whether the other person

1 removing demand information would reduce collusion and,
2 here, we have a graph of -- on the Y axis is a measure of
3 collusion and on the X axis are the periods the subjects
4 played with. The dotted lines and the gray lines, I'll
5 get to that in a minute. But the interesting thing here
6 is that we should expect the blue line, which is the full
7 information, perfect demand, full information treatment,
8 which has perfect demand information and monitoring, we
9 should expect it to have the highest collusion. But it
10 actually turns out that it is the medium one.

11 In other words, when we go from perfect demand
information, we removeminute.6s, knd the gray line the medium one.c

1 on one of these strategies, and also one for Rotemberg
2 and Saloner.

3 The random strategies just including our
4 constant just basically says you choose to collude or
5 deviate by flipping a coin. And the question that I ask
6 of the data is how well do all of these strategies fit
7 the data.

8 So, each column here has each of the
9 strategies, and I'm going to focus on the load likelihood
10 value that is at the bottom. And you can see that the
11 Rotemberg and Saloner strategy and, also, the Green
12 strategy perform best here, which I consider as a
13 relatively not strong but somewhat supportive of
14 Rotemberg and Saloner predictions.

15 Remember, these are tests on individual
16 strategies. We can also do a test on outcomes, which
17 would be the pair of strategies that firm chose in every
18 period. What we find is that we create an indicator
19 variable for each of those outcomes. In both letters,
20 you see that the errors outcome would be both firms
21 colluding when they're supposed to and zero otherwise.
22 In parameterization one, that predictor does relatively
23 well predicting 50 percent of the choices or the outcomes
24 correctly. And in parameterization two, interestingly,
25 they always collude at equilibrium, which is the one that

1 we're supposed to be observing, predicts 71 percent of
2 the outcomes.

3 Now, the Green and Porter theory, remember that
4 is known as a theory that triggers price wars after a low
5 demand shock. So, the gray lines that you see there
6 represent periods when a low demand shock was observed,
7 and we do see some drops in collusion or cooperation here
8 when that happens. But we really don't see that pattern
9 for which Green and Porter are known, finite regression
10 to the Nash equilibrium and then back up.

11 So, we do a little bit more of individual
12 analysis and we compare the Green and Porter strategies
13 to other strategies. In this case, the strategies are
14 going to be slightly different because since there is an
15 imperfect signal, they really do not observe what other
16 people are doing, we're going to be talking about
17 thresholds. And the imperfect signal is the implicit
18 price that they observe.

19 I consider two types of thresholds, one in
20 which firms revert to the Nash equilibrium after they
21 observe a low price and the two threshold strategy where
22 they revert back up to the collusive level after they
23 observe a sufficiently high price.

24 This is just a subset of the results, but here,
25 I just want to point out that the Green and Porter

1 equilibrium -- remember that it has many equilibria. But
2 the one that predicts data best is the one that has N
3 equal to infinity which is you deviate or start a price
4 war of infinite period after price or the signal falls
5 below a threshold level. And other threshold strategies
6 explain data relatively well, too. But with the feature
7 that firms stand, or in this case, subjects stand to
8 start price wars of infinite length.

9 The test on outcomes, which is similar to the
10 one that I did for Rotemberg and Saloner, tells us a
11 little bit of the same story then the individual
12 strategies. Green and Porter, with infinite price wars,
13 predicts relatively well our data.

14 And just to wrap up, because I think I ran out
15 of time, monitoring -- in this particular setting,
16 monitoring appears to matter the most. So, when we
17 remove monitoring, collusion drastically diminishes.
18 This doesn't happen with demand information. When we
19 remove demand information, collusion either stays the
20 same or it increases, which is a little bit
21 counterintuitive, but in line with the theoretical
22 predictions for this particular setting. I think both
23 theories have some support in the data. But the data
24 kind of tells us that strategies tend to follow a Green
25 strategy.

1 equilibrium.

2 That's something that theorists have something
3 -- it's difficult to have really little to say about.
4 And we know, certainly empirically, it's hard to say
5 something.

6 So, I think this is a very well-motivated paper
7 in that it's using experiments in an area where we do
8 need some more insight and certainly theory has not been
9 able to deliver that.

10 In terms of kind of the main take-aways to me,
11 one -- I think it really comes down to this, that kind of
12 pseudo-tastic collusion -- I say pseudo because -- and
13 I'll come back to this point -- in that at the beginning
14 of the experiments, there are some messages that are
15 allowed to be conveyed between the subjects. But there
16 are no messages over the course of the experiment, just
17 preplay.

18 But, to me, the big take-away is that, in
19 pseudo-tastic collusion, you know, you can collude with
20 demand volatility. Actually, I think it's somewhat
21 impressive that subjects were able to collude in the low
22 to medium states, but not in the high demand states when
23 it was appropriate for parameterization. But that with
24 imperfect monitoring, it's a lot harder to collude, which
25 leads me to kind of pose a question which I would put

1 forth as a possible further treatment or another set of
2 experiments, which posed the question of, when is -- if
3 you ask the question of when is it that it's particularly
4 valuable to explicitly collude, then I'm starting to
5 think for these experiments that, well, maybe when
6 imperfect monitoring is a real problem.

7 And we certainly know from a lot of different
8 cartels that they have spent a lot of time and energy in
9 terms of monitoring. Lysine, vitamins, a whole bunch of
10 them, they went to a big effort to engage in monitoring.

11 Now, here we -- I mean, these experiments can't
12 deal with this question because you really need something
13 where you have ongoing messages, but I think it's an
14 important issue to address, which I'll come back to.

15 So, there's kind of two just points I want to
16 raise about trying to kind of better understand the
17 results. One is to understand the fact that there's a
18 declining frequency of collusion. If you look at the two
19 graphs, the one on the left is for the Rotemberg and
20 Saloner full information treatment; the one on the right
21 with the Green and Porter imperfect monitoring treatment.
22 It's much more distinctive with the imperfect monitoring.
23 But, generally, there's just decline in the frequency of
24 collusion. So, I'd really like to better understand to
25 what extent that's an end game effect or to what extent

1 that, for example, that they're using a grim punishment
2 and we're just observing an accumulation of cartels that
3 have collapsed.

4 A second point is about these messages. I
5 mean, it kind of lets you know what was -- the types of
6 things that were allowed for. So, at the start of the
7 experiment, each of the players could choose a message
8 from a limited set that might say, I'm going to play low
9 every period, I'm going to play high every period. I
10 will play low if only a few play low and so forth. And I
11 can understand why you did that in order to be able to
12 get more collusive equilibria. It would be helpful to
13 report the results and how they related to the messages
14 so that we can better understand the role of those
15 messages. And, in particular, to what extent behavior
16 was tied to whether those messages coincided.

17 I have kind of two comments about equilibria.
18 One is dealing with this point here, this -- I'm quoting
19 from the paper here, "contrary to conventional wisdom,
20 removing demand information does not decrease, in some
21 cases, it increases collusion." Just to kind of review
22 on that, what he's contrasting is a treatment where it's
23 -- a la Rotemberg and Saloner, you observe the demand
24 realization prior to choosing your action. The
25 alternative is you observe the demand information after

1 the end of the period. So, monitoring is perfect in both
2 cases.

3 Now, to me, I don't know exactly where the
4 conventional wisdom came. To me, it's not surprising
5 that you get more collusion with the ex post demand
6 information because if subjects are -- certainly if
7 they're risk neutral, you're just looking at something
8 which is equivalent to determine a demand model. It's
9 just where you have expected demand instead of
10 deterministic demand. But it would be equivalent.

11 So, then, if you contrasted deterministic
12 demand with a Rotemberg and Saloner treatment, I would
13 suspect deterministic demand would -- collusion would be
14 zero. So, you're finding that with a theory which is, I
15 think, fully consistent with this.

16 The other issue concerns equilibrium and --
17 okay, so what was stated, delta equals -- it should be
18 .75 here. That was kind of changed over the set of
19 experiments. So, what he's done is assume that there's
20 30 periods for sure and then we're going to start having
21 random determination of -- at the end of the game.

22 Now, in characterizing what are the equilibria,
23 he uses the discount factor of -- he uses that of .75,
24 actually not .8. Now, the question is, is that
25 appropriate given the fact that the discount factor is

1 one over the first 30 periods of the game? Let's just
2 focus on parameterization one. I think that is
3 appropriate for the imperfect monitoring treatment
4 because, in that case, when delta is .75, when you get to
5 period 31 and your discount factor is .75, you cannot --
6 the Green and Porter strategy is not in equilibrium and
7 thus, through kind of an unraveling argument, you're not
8 going to be able to sustain that as an equilibrium for
9 any of the first 30 periods as well. So, it's fine
10 there.

11 Where it's more of a problem is with the full
12 information treatment because, under the
13 parameterization, what you show is when delta's .75, you
14 can collude in the low and medium demand states, but not
15 the high demand states. Now, that may be true when you
16 get to period 31, but it isn't clear to me that it's true
17 early on in the horizon when the discount factor is one.

18 Just in terms of future directions, one thing I
19 think it would be interesting to do would be allow for a
20 public correlation device. I mean, in essence, you have
21 that with the full information treatment, which is
22 through the demand. Now, the demand's also affecting the
23 pay-offs but you can also use it as a public correlation
24 device.

25 It would be interesting to have that in the

1 imperfect monitoring treatment because one of the things
2 that you find that's difficult is that once subjects stop
3 colluding in imperfect monitoring, they have a hard time
4 getting back to collusion. And you find the grim
5 punishment is actually the best fit. If there's a public
6 correlation device, that might allow them to get back to
7 collusion.

8 The other thing I'll just mention is related to
9 something I said at the beginning, which is kind of a
10 broader point. I think a really important area for
11 experimental work in relationship to IO is to get at this
12 issue of explicit versus tacit collusion, specifically
13 when is it particularly valuable that firms explicitly
14 collude, engage in direct communications as opposed to
15 tacitly collude. That's something which we have a very
16 hard time providing any insight on theoretically.

17 Where I think it can be done experimentally is
18 we look at a host of different environments. For
19 example, here's two environments looked at by -- three
20 environments looked at by Christian. And then to look at
21 those under two treatments, one where they aren't any
22 messages over the course of the experiment and one where
23 there are messages, and you have to be somewhat specific
24 about what kind of messages you're going to allow for.

25 But those types of experiments would be able to

1 start getting at the question of when is it that we
2 really think it's important to firms that they engage in
3 direct communication? When does it have a lot of value?
4 So, I'll stop there.

5 MR. SHAPIRO: Thank you. Again, there's a lot
6 here. Are there some questions if you want to voice them
7 at the microphone?

8 ()

9 MR. SHAPIRO: All right. Well, please join me
10 in thanking all the panelists.

11 (A)

12 MR. SHAPIRO: I guess Chris will tell us what
13 we do next.

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A E E / / : EC / C / F 5 AC A D

1 Corporation who's going to -- she's an attorney and she's
2 going to be speaking about privacy issues in online
3 advertising.

4 MS. GLUECK: This is always the challenging
5 moment because I'm from Microsoft. If I make a mistake
6 now, my credibility is destroyed.

7 So, what I'm going to do is try and set the
8 stage so we can have a discussion about whether
9 regulation really makes sense from an economic
10 perspective for privacy on the Internet and, more
11 specifically, for online advertising. So, I'm going to
12 explain to you how it works and, hopefully, maybe even
13 scare you a little bit. I know it's towards the end of
14 the day, so I need to keep you awake.

15 We'll start by talking about the players.
16 Advertisers, you know, those are the ads that you see
17 when you visit Web sites, particularly when you go to
18 visit free Web sites, like maybe you read your newspaper
19 online so you don't actually have to pay for it. Well,
20 it needs to be paid for some way.

21 So, the deal you're actually making is to see
22 some advertising in exchange for free content.
23 Oftentimes, that advertising is provided by a third-party
24 ad network that provides you advertisements as you move
25 around the Internet. Now, there are a number of them,

1 but the same ad networks do see you as you visit various
2 Web sites. So, I'm going to walk you through some
3 scenarios so you can see how this works and what data
4 gets collected.

5 The simplest scenario is when an advertiser
6 just wants to buy some inventory or add impressions on a
7 single site. So, the only data that the ad network
8 server needs in that scenario is the IP address of the
9 user, because, of course, that gets left behind every
10 time you go anywhere on the Internet. So, the first
11 party site that you visit, in this case, it's Kelly Blue
12 Book, they get your IP address. But the ad server gets
13 it as well. They see where you've visited, the KBB.com,
14 and the time of your visit and they track what ad that
15 you saw at that point. Pretty simple.

16 It gets more interesting when the advertiser is
17 buying inventory on multiple sites. Let's just suppose
18 that they only want to show a particular ad once to any
19 particular customer. So, they want everyone to be net

1 and when.

2 Now, you're visiting MSN.com. They're not
3 going to show you that ad again. They're going to show
4 you a different ad. They know this from the cookie ID
5 and from the other information about where you've been
6 and where you've seen ads from that particular ad
7 network. Over time, this accrues. So, the places you
8 surf that are served by the same ad network wouldn't
9 necessarily even need to be an ad network. If you see
10 the same weather information on a website, that's coming
11 from another server somewhere. That server knows that
12 you visited three sites today and saw their weather on
13 all three of those sites.

14 For targeting, sometimes what you want to do is

1 cost, and I started to notice that wherever I went, I was
2 seeing ads for cars. The interesting thing is fairly
3 quickly that went away because within a certain number of
4 weeks, most people make their car purchase decisions.
5 So, they don't show you those advertisements anymore
6 because you're probably sick of looking at cars. You're
7 done with that.

8 So, you are getting some value there.
9 You're seeing advertisements that are more relevant to
10 your interests and what you're looking for. You know, if
11 you're shopping for a camera, those decisions are usually
12 made very quickly, I think within a week or so. So, you
13 couldn't see camera ads or cell phone ads for too
14 terribly long.

15 I think this is something that people generally
16 don't -- none of my friends knew about this until I
17 explained it to them. Let's say you go to Walmart.com
18 and you put some stuff in your shopping cart. Walmart
19 advertises on a lot of Web sites. So, what they do is
20 instrument their Web sites as the publisher. They
21 instrument their Web sites so a Web beacon indicates
22 that, hey, this is a Walmart shopper and let's say you
23 abandoned your shopping cart and, in this instance, it
24 was full of maternity clothes, that way the ad network
25 can know that about you. You're someone who shops for

1 maternity clothes and someone who shops at Walmart. So,
2 then when you go to some other Web site, you're going to
3 see an ad for Walmart to try to bring you back to finish
4 that purchase.

5 Meanwhile, this data continues to accumulate.
6 Where you go -- and don't worry, I'll tell you how to
7 make it stop in a couple of minutes.

8 () .)

9 MS. GLUECK: You know, where you go, what
10 you're interested in. This may even include some
11 registration data that you gave when you were registering
12 on a Web site. So, for example, if you register for a
13 Windows Live ID because you have a hotmail account or you
14 use MSN Messenger or something like that, we collect a
15 little bit of demographic data about you. I think gender
16 and country and something else that's not popping into my
17 head. Pardon? Age, thank you. Although you don't
18 always get asked age. It depends on where you are
19 in the process. But a lot of times age so that we can do
20 the COPPA screening if a child hits something that would
21 be -- where COPPA is relevant.

22 So, we're very careful to take that demographic
23 data we have about you and we associate it with a number,
24 but we never associate it back. So, your name, your
25 hotmail email address, any other email address you

1 provided us, that's never associated with the advertising
2 data. I can't tell you how everyone does it, but I think
3 we're somewhat unique in that system, and I'll tell you a
4 little bit more about that later because it helps to make
5 our opt-out of targeting advertising cookie a little bit
6 more effective.

7 So, as you think about this, we saw a lot of
8 different types of data that was accumulating in the
9 profit and associated with a cookie ID. Over time, you
10 know, if you know enough about a person, they may become
11 more and more identifiable. Search queries, that's
12 something else that could be in a profile, and Pablo will
13 be talking about that later and how that works.

14 So, if you think about it, well, gee, is this
15 really a big deal? A lot of this data is pretty
16 innocuous. Well, if all third-party ad networks were
17 sort of created equally and, you know, this ad network
18 had a little bit of data about you and that one did, it's
19 probably no big deal. But as the ad networks themselves
20 have more and more market share, then they know more and
21 more about you. They may not know your name, but they
22 certainly know a lot about your habits.

23 DoubleClick, I believe, is the largest in the
24 market. I think they have about 70 percent. They're
25 owned by Google and Google also has AdSense, which is

1 another advertising serving mechanism. So, Microsoft has
2 a sizable network as well. It's called Atlas. So, over
3 time, you know, companies are accumulating more and more
4 data about users, which raises, of course, some privacy
5 concerns.

6 I'm always asking, as I visit Web sites, well,
7 gee, what are they doing with my data? How long do they
8 keep it? Do they anonymize it? And if they anonymize
9 it, what method do they use to anonymize it? At the end
10 of -- we retain search data currently and advertising
11 data for up to 18 months. At that point, the IP
12 addresses are all completely wiped out. The cookie IDs,
13 any cross-session identifiers are completely wiped out.
14 So, we don't know -- we know somebody searched for maybe
15 this address, but we don't know who it was or what other
16 things they searched for at the end of that period.
17 Different companies handle this in, of course, different
18 ways.

19 I really started thinking a lot about
20 anonymization when back in 2006, AOL had a data breach
21 where a well-intentioned researcher posted 650,000 users'
22 search data over a -- from three months of search data
23 from that many users, which turned out to be about 20
24 million searches. And they took out the user names so
25 that, okay, I've anonymized the data. Well, there were

1 still cookie IDs. So, if I had done 200 searches during
2 that three months on AOL, then you would know that User
3 12345, what all I had searched for.

4 It turns out a disturbing number of people in
5 the United States are thinking about killing their
6 spouses from looking at the searches. I am completely
7 serious.

8 (.)

9 MS. GLUECK: Or maybe they're writing murder
10 mysteries. If you're a glass half full kind of person,
11 maybe there's a more positive spin you can put on that.
12 Two people were identified fairly easily by the press.
13 So, here we have this anonymized data. People were
14 identifiable. There were other examples. After the
15 session, I can regale you with them all night long. But
16 it really makes you wonder how anonymous is anonymous and
17 how much do you know about what people are doing.

18 Well, the industry is self-regulated. The
19 Network Advertising Initiative in 2002, but thanks to
20 some concerns about DoubleClick, was formed. Atlas, our
21 ad network, was one of the founding members, I believe.
22 And there are rules for how you do these kinds of things,
23 what kind of consent you need to get from people, for
24 example, if you're going to advertise to them based on
25 sensitive information like health, that you get consent

1 for doing that, because that's a little -- you know, just
2 because a friend tells you they're sick, you look up a
3 medical condition and, suddenly, you start seeing these
4 ads, that would be a little creepy.

5 So, the FTC, this year, proposed guidelines,
6 which is great because, you know, after six years, that
7 seems very timely to take a look and say, does the
8 industry still look the same, are the players still
9 really the same, you know, what about inspection. There
10 are new questions today. And, so, they've proposed
11 guidelines for self-regulation. Three states have
12 proposed legislation, New York, Connecticut and
13 Massachusetts. And I have to say the legislation is
14 pretty well-crafted. Clearly, they had an understanding
15 of how the business works, how the technology works and
16 what data we're talking about.

17 In Europe, we think they'll probably turn to
18 this next, they've been -- the data protection regulators
19 have been very focused on search, and so, it's sort of
20 the logical next thing for them to start looking at.

21 So, I should have disclosed at the beginning,
22 I'm not an economist, I'm a lawyer. And I apologize, I
23 have no charts or graphs for you. But, you know, I start
24 to wonder how much users understand about their privacy.
25 I mean, how much did everyone here, did you know that

1 it's possible that you were being tracked? Well, the
2 good news is, there are things you can do about it.

3 If you go to the NAI website, you can go and
4 opt out of all the member ad networks at one time. So,
5 you can see this is just the very beginning on the screen
6 shot, of the list of networks you can opt out of being
7 targeted. Your information may still be collected, but
8 they don't use it to actually target ads to you.

9 Internet Explorer lets you control cookies.
10 It's a little hard to live in the world and use the
11 Internet without accepting any cookies. So, I think
12 that's a little harsh perhaps.

13 Reading privacy statements, always helpful.
14 We're big fans of the layered notice approached where you
15 provide meaningful detail at the top layer. In this
16 instance, you can go directly to our display of
17 advertising section from the top level and learn how to
18 opt out of getting advertising from Microsoft, but
19 targeted advertising from Microsoft. You'll still see
20 sort of generic ads coming up, but the ones that are just
21 for you because you are a woman who -- if you're me,
22 you're a woman who's 46 years old and that kind of
23 advertising stops.

24 The neat thing about our opt-out, if you check
25 the top box, then it's just like everyone else's and if

1 you're a little paranoid about your privacy and you
2 delete your cookies regularly, then your opt-out cookie
3 goes away, too, and it's very sad, you start to get
4 targeted advertising again.

5 If you check that second box and you have a
6 Windows Live ID, then every computer you log into using
7 your Windows Live ID, the targeting will stop. If you
8 get rid of all your cookies, all you need to do is log
9 back in, which you might be doing to check your hotmail
10 or, you know, just -- I don't think people log back in
11 just to set the cookie. I think they do it as a natural
12 part of doing other things. But it sets the cookie all
13 over again. I believe this is unique in the industry.

14 Internet Explorer 8, we realized the beta
15 version of this some months ago, and it's got this new
16 thing called in-private blocking, that lets people block
17 third-party content. So, it's not just ads. It's a map,
18 a stock ticker, the weather, things that aren't coming
19 from the website you think you're visiting, you can block
20 or you can choose to always allow, which, you know, I
21 personally think it's a good deal to get to see free
22 content in exchange for advertising. So, I'm not
23 blocking anything at the moment. But it's nice to know
24 that I could because I'm using the software.

25 The difficult part in working with the --

1 because I support this product -- in working with the
2 team was how do you explain to end users what they're
3 blocking and what they're allowing when they don't have
4 the faintest idea, some of them, that third-party -- a
5 lot of first-party Web sites serve third-party content?

6 So, again, we're sort of back to that question
7 of, you know, regulation, does regulation make sense in
8 this area? And it may. Of course, if it took into
9 account how the industry works, how the technology works
10 and allowed for the ability to use data and innovate
11 using data, you know, good regulation, might make sense
12 to help protect consumers. Bad regulation, I think,
13 would just hurt the industry.

14 MS. ATHEY: So, why don't we keep moving
15 through the panel in the interest of time and then we'll
16 come back and have questions for everyone.

17 MS. MILLER: Mentioning regulation is a good
18 segue for what I'm going to talk about. I'm just going
19 to spend a few minutes telling you about some of the
20 results from some research that I've done with Catherine
21 Tucker at MIT, looking at the effects of privacy
22 regulation at the state level on the diffusion of a
23 particular form of health information technology, in
24 particular, electronic medical records.

25 So, there's sort of this question about good

1 regulation, bad regulation. In some sense, we want to
2 ask, looking at the regulations that have actually
3 happened and that exist at the state level, about half
4 the states in the U.S. currently have some form of
5 additional requirements that restrict the ability of
6 healthcare providers to share information that they have
7 among each other without express consent from patients.
8 So, if you have some private medical information that
9 your hospital knows about you, half the states have some
10 extra standards above the federal minimum standards
11 protecting the privacy of that information.

12 We want to look at what happens or what's the
13 effect of these regulations on the diffusion of
14 electronic medical records. Electronic medical records
15 are this technology that basically allow you to use
16 computer systems instead of paper records to keep track
17 of, so to store medical information, to retrieve it
18 within a hospital. But also one of the key benefits from
19 this technology, one of the key promises is the ability
20 to exchange information across healthcare providers
21 faster and more cheaply.

22 So, when you think about what privacy rules
23 might do to the diffusion or to the benefits from the
24 point of view of a hospital of switching over to
25 electronic records, you can imagine sort of two possible

1 scenarios. It's possible on the one hand that regulation
2 is inhibiting diffusion. The way that that would happen
3 is that the regulation puts a cost -- every time you want
4 to share information or share information, privacy
5 protection can make that more costly and more difficult.

6 So, if you're thinking about adopting, you
7 think about the network benefits, the benefits that you'd
8 have from other local providers or even more distant
9 providers who also have electronic records, that benefit
10 of being able to exchange information about patients more
11 easily is going to be reduced when you have to overcome
12 an institutional or regulatory burden. So, that
13 regulatory burden is going to replace the burden you had
14 in terms of the physical challenge of exchanging this
15 medical information and might make hospitals less likely
16 to adopt medical records.

17 On the other hand, it could be that patients
18 are very concerned about privacy. They might be
19 concerned for reasons that Sue mentioned. They might be
20 concerned about having their identity stolen. Medical
21 identity theft is a new phenomenon. They might be
22 concerned about having their neighbors or coworkers find
23 out about health problems that they have that might be
24 embarrassing. So, they might not want to go to a
25 hospital that uses electronic records. They may not want

1 to have their information stored in a way that could be
2 easily accessible or that may be more vulnerable to
3 exposure.

4 In that case, it could be that when a state
5 comes in and says we're going to protect your privacy,
6 we're going to put some strong regulation in place, that
7 might make consumers feel more comfortable and more safe
8 with electronic records and that might promote adoption.
9 So, there's sort of this potential cost or benefit and we
10 don't really know what the net effect is going to be.
11 And what we do in our paper is we try to empirically
12 assess which is, in fact, the case.

13 Just a bit of background in terms of why we're
14 interested in electronic records in particular, this has
15 been something that politicians in the U.S. have been
16 talking about for a very long time. Healthcare
17 information technology and electronic records, part of
18 that has been lauded by politicians across the spectrum
19 as this great technology, this great innovation that's
20 going to both reduce costs and improve outcomes.

21 So, we have a quote from Newt Gingrich and
22 Hillary Clinton both agreeing that healthcare IT is

1 around for decades since the '70s and adoption in the
2 U.S. is still pretty low. Under 50 percent of hospitals
3 have switched over to electronic records. This is a
4 concern, and so, we want to know if privacy is having a
5 role in terms of either -- possibly slowing that
6 adoption.

7 This is just more stuff about why -- so, this
8 Bush Administration had a target of national EMR adoption
9 by 2014. People are skeptical about whether or not that
10 will happen. The Federal Government's been very
11 concerned about privacy. Consumers have expressed
12 concerns about privacy for electronic records. The
13 government attention, to date, has been to try to figure
14 out how to make privacy standards tough enough. So,
15 there's a \$17.3 million study that was trying to assess
16 how can we ensure privacy.

17 There's a lot of media attention that talks
18 about kind of what happens when privacy fails and when --
19 especially information about celebrities is disclosed.
20 So, George Clooney was in a motorcycle accident and
21 everybody heard about it. Britney Spears went to rehab
22 and we knew about it. But there's not a lot of
23 discussion about what the potential costs are from
24 imposing strong regulation.

25 And the particular cost that we're thinking

1 about is this trade-off where strong regulation that
2 protects privacy might be blocking these network effects
3 from sharing medical information. As far as we know,
4 nobody's looked at the other side of this and that's what
5 we're trying to contribute.

6 There is some anecdotal evidence, other than
7 our study, that has -- where vendors have said that
8 strong privacy laws can be a challenge and, also, medical
9 providers have sometimes said that complying with
10 complicated state regulations, in terms of protecting
11 privacy, have led to a particular regional effort to
12 combine and share health information. In Southern
13 California, it actually fell apart after several years
14 and a lot of money went into trying to create it and the
15 regional initiative fell apart and the large -- and the
16 participants mainly blamed the challenge of trying to
17 comply with the strict California state privacy rules.

18 So, in terms of everything that I'm going to
19 talk about now, our results -- our empirical study is
20 looking at this particular technology, healthcare IT. We
21 think that some of these trade-offs in terms of privacy
22 and technology adoption might have some implications for
23 other types of technologies where there are network
24 benefits that have to do with sharing information.

25 So, the data that we have, we basically need

1 data on two components. One is the adoption decision.
2 And we get that from the HIMSS Dorenfest database. So,
3 we have data on adoption through 2004. And we can match
4 that with some information from the American Hospital
5 Association to learn a bit more about the hospitals.

6 The period that we look at is from the 1990s
7 through the end of 2004, into 2005. And you can see that
8 that's the period when most hospitals in the U.S. are
9 adopting. This is just a histogram of the number of new
10 hospitals adopting and that 1992 bar is the total number
11 of hospitals that adopted in '92 or earlier. So, really,
12 this is the interesting time period to be looking at to
13 study adoption of EMR.

14 Then we need to combine that with some data on
15 privacy laws, which we get from a group of Georgetown
16 University called the Health Privacy Project, whose
17 function is really to understand privacy laws and, also,
18 to advocate for stronger privacy protection and consumer
19 protection. So, we get laws from them. We have a panel
20 of laws. This is just the cross-section in 2000, so you
21 can see that there's a lot of variation. About half the
22 country, half the states have a law; half of them don't.
23 There's no obvious red state, blue state configuration.
24 All kinds of different states in all different regions,
25 some of them have and some of them don't have privacy

1 Alessandro just a minute to get his presentation loaded
2 up. So, now we've heard about two specific places where
3 information can be used to provide a lot of benefits and
4 privacy laws can potentially get in the way of that. Now
5 we're going to hear a little bit about how consumers
6 think about privacy and whether they actually understand
7 what they're getting into. Then, finally, we'll hear
8 from Google about some of the -- as they kind of pull
9 some of these ideas together.

10 MR. ACQUISTI: So, my research focus, I call it
11 the economics of privacy and the behavior of economics of
12 privacy. It's a study of the trade-offs associated with
13 the protection and the revelation of personal information
14 and the study of how individuals make decisions about
15 those trade-offs, decisions that sometimes may sound
16 contradictory or even damaging.

17 In fact, let me start with one shot from the
18 Daily Mail 2007 about a Facebook group called 30 Reasons
19 Why a Girl Should Call It a Night. So, Facebook is an
20 online social network on which 90 percent of our students
21 are, and no longer only students, also people after
22 college are on Facebook. What is interesting is that not
23 only people reveal personal information such as birthdate
24 and sexual and political preferences, but in some cases,
25 they also reveal information which could be embarrassing

1 or damaging.

2 In this particular group, ladies post photos of
3 themselves in various states of being passed out or drunk
4 and sick from drinking and so forth. It's not angry,
5 angry ex-boyfriends posting this information. It's the
6 person herself posting this information.

7 So, why? We could conclude that the Facebook
8 generation has no sense of privacy whatsoever, no need
9 for privacy.

10 (.)

11 MR. ACQUISTI: But, in fact, that's not really
12 necessarily the case because pretty much at the same time
13 when the article was published in the Daily Mail, also in
14 2007, this other article came out about the Beacon. You
15 may remember Facebook started pushing for this
16 advertising program called Beacon, which would gather
17 more information about Facebook users and spread it
18 around to other Facebook users. Sure enough, around
19 700,000, apparently, Facebook users reacted violently
20 against the Beacon and forced Facebook management to go
21 back in their plans of pushing for these Beacon
22 strategies.

23 So, what we have at the same time, we have some
24 need for publicity, even bad publicity, and the need for
25 privacy. They seem to be contradictory needs, but, in

1 fact, they exist in each or every one of us and they only
2 show control. Privacy is often defined as a control on
3 what is public and what is private. But, for myself, my
4 background is economics. I can really control this
5 initial signaling.

6 The lady who's publishing photos of herself
7 passed out and drunken is signaling information to a
8 certain peer group, right? To a peer group in which
9 being passed out means that you can party hard, you're a
10 fun person and so forth.

11 Well, the problem is that you don't have
12 control of the information once it's put out there. You
13 no longer can know who else will see that information.
14 Maybe your parents, maybe your future employer. Maybe
15 that information is cached somewhere, and 20 years later,
16 when you are going for Supreme Court candidate or maybe a
17 Vice Presidential candidate, the photo pops up again.

18 So, there are costs and benefits in revealing,
19 as well as protecting information. That's what the
20 economics apprise us about. It's not new. Chicago
21 School economists were the first dealing in this area --
22 with this area, Stigler and Posner, but yet they --
23 Chicago approach which was privacy sometimes creates
24 inefficiency in the marketplace because it reduces
25 information. Varian, Noam, Laudon in the mid-'90s

1 introduced more IT expertise into the economics of
2 privacy. And then, more recently, after 2000, a number
3 of people, (inaudible) Taylor at Duke, (inaudible) Pavan
4 and myself (inaudible) and Calzolari (inaudible)
5 Berkeley, started working with microeconomic models of
6 privacy, especially privacy (inaudible).

7 But as we were aptly modeling a way, we were in
8 a two-peer model, we have a high and low consumer buying
9 goods and (inaudible) tracking them and trying to learn
10 personal information to (inaudible) them, we learned also
11 something surprising, which although people were claiming
12 that privacy is important, you need more privacy, if I
13 had more privacy, it would show up more aligned. If I
14 have more privacy, it would go more aligned. In fact,
15 behavior did not reflect those attitudes.

16 So, we started discovering, as we were doing
17 these models, that reality was telling us that people
18 want privacy, but they don't want to do anything about
19 it. They rarely pay for it. In, fact they can be
20 convinced very easily to clear away lots of personal
21 information for a small reward. This was shown by
22 (inaudible) Spiekermann in Germany.

23 More recent studies that we did on online
24 social networks showed a clear dichotomy between what
25 people say they want to keep private and what they do on

1 online social networks. Leading many people to say -- to
2 ask, so, do people really care for privacy? Is it
3 something that is important? And if people care about it
4 and they don't do much about it, should we be (inaudible)
5 enough to take their own protection, so the FTC or
6 policymakers or businesses should protect what consumers
7 are not protecting themselves. So, how can we answer
8 that question?

9 Well, this trying to answer the question led me
10 to engaging into behavioral economics of privacy.
11 Because I realized that taking a fully rational approach
12 here would not address all the issues. The fully
13 rational approach would be the one in which Johnny
14 MySpace is thinking whether he should reveal or not
15 certain particular sexual kinks on MySpace. And he's
thinking that, well, if I do so, I will find somebody who

1 flyer which was handed out at the San Francisco pier when
2 I was a student there, so around 2002, 2003. And it asks
3 people personal information, to fill out this form
4 indicating age, mental status, occupation, income, credit
5 card, even address. In exchange for participating in a
6 lottery with the odds of one out of 700,000, winning
7 around \$25,000. So, there are economists here, so you
8 can easily do the expected value. It's basically a few
9 cents. Not even worth the actual opportunity cost of
10 spending time filling this form out.

11 But the problem is when people see this form,
12 how can we make it a truly rational decision about what
13 is the best approach. Should we fill it out or not?
14 What is the difficulty of making this decision?
15 Difficult framing, that even if we care about privacy, we
16 care about privacy in general. In the specific, well,
17 yeah, with specific benefits and specific costs, we may
18 say we want to protect ourselves, but then we don't want
19 to spend time maybe changing the privacy settings or the
20 cookie settings on the browser. They are there and they
21 cost only 10 seconds to change, but those 10 seconds are
22 too much.

23 Incomplete information, so things that we don't
24 even know that the problems are there and we don't know
25 that the solutions, such as changing the cookie settings,

1 are available.

2 Boundary rationality, Facebook has a very
3 granular -- gives very granular control to users to
4 decide what to reveal to whom and when. It's almost too
5 granular, in the sense that behavioral economists know
6 the paradox of choice. That sometimes when you give an
7 incredible amount of different sections to choose from to
8 users, the final decision could be sub-optimum.

9 And, finally, even if we had complete
10 information (inaudible) there are all these psychological
11 behavior biases that experimental behavior economists
12 have studied over many years that seem to all apply to
13 privacy decision-making. Indeed, in my final minutes, I
14 will show you one particular study of the many we're
15 doing with George Lowenstein and Leslie John (inaudible),
16 one particular study in which we basically take one idea
17 from behavioral economics and we apply it straight to
18 privacy.

19 So, the first two, I will not discuss because I
20 don't have time, but they are about how you can frame
21 differently a certain survey or certain questions and
22 impact the propensity of people to reveal personal
12 information, as we

14pWwe thch we ,time, stTDpeople -2 personal

1 protected, they start lying and revealing less probably
2 because they become frightened and (inaudible) about the
3 sensitive (inaudible).

4 The study we focus on is on the effect of
5 framing of privacy (inaudible). So, this is the story.
6 So, basically, it's a traditional endowment study, only
7 that we tried to translate a downward study into privacy
8 (inaudible). In privacy, you have willingness to pay and
9 willingness to offset. You are willing to offset money
10 for your privacy when you're searching information on the
11 Internet because you are using a service, but you are
12 revealing information about yourself. Your IP address,
13 your interests and so forth. You are exchanging
14 something for your data.

15 But sometimes the results (inaudible) protect
16 when, for instance, you decide to go and delete your
17 cookies. There is an intangible cost, the time you spent
18 to clean up your system, that's the cost that you are
19 offsetting to engaging.

20 So, the framework we wanted to use to study
21 this problem was -- and this was an experiment we did in
22 the field. We stopped people in the mall and then
23 randomly assigned these people to different groups. In
24 one group, we told people, hey, would you like to
25 participate in a study, and if you participate in this

1 study, you will get this gift card that you can use where
2 any debit or credit card is accepted. By the way, this
3 gift card is worth \$10 and it's anonymous. Whatever you
4 purchase with this card, we will never know, nobody will
5 ever know.

6 Then there was a study which was completely
7 unrelated to us. We didn't care about the actual study.
8 And then something (inaudible).

9 To another group, experimental group, instead
10 we said, hey, would you like to get a gift card to
11 participate in this study. The gift card is valued at
12 \$12 and your name will be recorded and the transactions
13 you make with this card will be known. People got the
14 card. Did another study. Again, this study was
15 completely unrelated to us. Eventually, each group was
16 offered to swap cards.

17 The first group who was given the \$10 anonymous
18 card was told, hey, by the way, thanks for participating
19 in the study. Would you like to swap your \$10 anonymous
20 card for a \$12 identified card? In other words, would
21 you like to get two more dollars to give away your data.
22 And the second group instead was told, hey, by the way,
23 look, you accepted this card, \$12 identified. Would you
24 like to swap it for a \$10 card which is anonymous? In
25 other words, this group was told, would you like to give

1 I should stop here and let Pablo talk next.

2 MR. CHAVEZ: So, next time don't show my
3 sister's profile.

4 MR. ACQUISTI: I didn't know your sister was
5 from the UK.

6 (.)

7 MR. CHAVEZ: Hi, good afternoon. So, first of
8 all, thank you very much to the FTC and also to
9 Northwestern University for giving Google the opportunity

1 approach to privacy, which is just, actually in many
2 ways, very similar to our approach to product
3 development. And, finally, hopefully, this serves as a
4 framework, not the framework, but a framework to look at
5 a potential privacy self-regulation regulation and
6 legislation that may be coming up. Just one way to look
7 at it.

8 Lastly, I guess a couple of things I'm going to
9 present might actually serve as good raw data for you
10 guys maybe for next projects. So, hopefully, it's
11 helpful in that sense.

12 So, first and foremost, Google, like companies
13 like Microsoft and others, is very, very focused on
14 innovating and we innovate through iteration, so
15 repetition and experimentation. That is also very much
16 our approach on a good number of privacy issues. When
17 I'm talking about privacy, really I'm talking about the
18 collection, use and retention of users' personal
19 information, so maybe narrowly defined.

20 In this case, what I'd like to talk about a
21 little bit is retention of our search logs. So, first,
22 I'll give you an explanation of search logs themselves;
23 secondly, I'll talk about our retention policies for
24 those search logs; and finally, I'll give you a sense of
25 kind of the other factors that needed to be taken into

1 consideration as we determined kind of the retention
2 policies.

3 So, very simply, if you were to go to
4 Google.com right now and type in a search, Federal Trade
5 Commission, for example, we would collect standard log
6 data, much like what Sue talked about and others have
7 talked about. This is the URL, including the search
8 query, in this case Federal Trade Commission, the IP
9 address associated with the device from which the query
10 originates, the time and date of the query, the operating
11 system of the device, the browser type, so I8, Chrome,
12 Opera, Firefox or whatever you happen to be using, and a
13 cookie ID.

14 I'll note, too, that this is a situation where
15 an individual has not signed in to Google. So, this is
16 an unauthenticated individual who's conducting a search
17 on Google.

18 So, what we've decided over time is to reduce
19 our retention or anonymization period for search logs for
20 server logs generally to nine months. What I mean by
21 that is that essentially, as you can see in this graphic,
22 which by the way, we presented our privacy policy just to
23 give users a sense of what exactly we're talking about.
24 We delete the last octet of an IP address associated with
25 search query after nine months.

1 Now, back to the iteration point, Google
2 started as a company that retained this data
3 indefinitely. So, the company's 10 years old now from
4 soup to nuts, from the moment of incorporation until now.
5 For about eight years of that time, Google was retaining
6 these logs indefinitely. Now, various stakeholders,
7 policymakers, regulators and others expressed concern
8 that, in particular, IP addresses were considered to be
9 personally identifiable information. Google, by the way,
10 takes a little bit more of a nuanced view. We believe
11 that IP addresses are PII, personally identifiable
12 information, in some circumstances and not in other
13 circumstances. I'm certainly happy to answer questions
14 about that.

15 So, we went from indefinite to about 20 months
16 ago a policy of anonymizing after 18 to 24 months.
17 Shortly after that, we went to a policy of 18 months.
18 And in September of this year, we went to a policy of
19 nine months. Essentially, it's taken time to really look
20 at the effects of these shorter retention periods on
21 various services that we provide, on security issues that
22 we have, on integrity issues that we have with the
23 system.

24 So, just to talk about a couple things, some of
25 you may be familiar in 2004, our system was attacked by

1 -- respectfully suggests the proper spelling for a query.
2 That is developed -- in part, one of the signals that
3 you're looking at is, for example, in a particular
4 session you could have somebody spell apple with one P
5 and then spell apple with two Ps and we know that the
6 device from which the query originated probably
7 misspelled it the first time and then spelled it
8 correctly the second time. That is then inputted as
9 essentially the correct spelling for A-P-L-E and it's
10 suggested in future instances of that misspelling. So,
11 it's a great improvement.

12 To me, though, what's really fascinating and

1 correlation between the search queries relating to the
2 three top candidates, in this case, Senators Obama,
3 Clinton and Edwards. So, whether there's any correlation
4 between those queries and actual results in the caucuses.

5 So, as you can see, what I looked at is United
6 States, subregion Iowa, January 2008. The caucus itself
7 was around January 4th. So, a couple of dash marks to --
8 well, to my right of January 6th. And really, really
9 interesting. You see that Obama -- so, Obama won 38,
10 Clinton got about 30 and Edwards got about 30. So, you
11 see Obama trended upwards significantly prior to the
12 caucuses. And really interesting, you see that Edwards
13 and Clinton were basically tied just like in the
14 electoral results.

15 So, this is just one application of Google
16 Trends, which uses, again, IP addresses to a certain
17 geography. You can see that we're geo-locating to the
18 level of city here in a very, very useful way to
19 consumers, in a very useful way to researchers. You can
20 imagine other applications, for example, looking at
21 health trends throughout the world, whether search
22 queries can actually tell you something about something
23 that has happened historically in the health area or
24 currently in the health area.

25 One other potential application is the effect

1 on the economy. Is there potentially a correlation
2 between searches for cars in, say, the eastern United
3 States and an up-tick in car purchases? Could that
4 actually tell us about an economic recovery? So, just
5 really, really fascinating data, again, tied to IP
6 addresses and IP addresses have been kind of the focus of
7 regulators and legislators as a potential area where
8 companies should be obligated to delete IP addresses
9 after some period of time.

1 principles -- was the motion that maybe we could actually
2 provide additional transparency and choice to consumers
3 when they receive one of these ads from a third party.

4 So, if you were to click on the ad itself up
5 top, the landing page would be for a product or a service
6 offered by that company. But if you were to click on the
7 links on the gray strip at the bottom, that could
8 potentially take you to a privacy policy, explaining what
9 data is collected and how it's being collected, or
10 potentially give you the opportunity to opt out of data
11 collection, or give you the opportunity to actually
12 comment on the ad and say whether you liked it, whether
13 you ever want to receive anything like that again.

14 So, again, this kind of experimentation, you
15 know, we would hope would be encouraged. This would be,
16 from our perspective, kind of a great tool to adopt for
17 industry at large. But this kind of an idea doesn't come
18 up without kind of the opportunity to really experiment
19 around privacy.

20 One last example of experimentation around
21 privacy, Sue had talked about privacy policies and
22 layered policies. We agree that those are great. One
23 area where we're experimenting is really kind of
24 expanding beyond the notion of a privacy policy and
25 really kind of talking about privacy center where we

1 associate kind of privacy practices and principles with a
2 particular product. That's a lot of Ps.

3 So, in this case, we have a privacy center
4 around advertising and privacy that talks about our
5 privacy principles relating to advertising, that also
6 explains products so people understand exactly what's
7 going on, that allows them to opt out of data collection
8 if they so wish.

9 Then, finally, and this, to me, is the coolest
10 thing, we've been working very hard on a series of
11 privacy videos, on YouTube videos. We actually have a
12 privacy channel on YouTube and we also feature the videos
13 in our privacy centers. That is a great -- that's
14 actually an experiment that's turned out really well,
15 because not only are we providing kind of five-minute,
16 ten-minute snippets, plain English explanations of
17 privacy, but also we're opening up these videos to
18 comments.

19 So, no longer are we talking about privacy
20 policies, specifically where it's a one-way conversation,
21 we're just pushing out information. But, rather, we're
22 collecting comments from our users, hearing from them
23 about what they like, what they don't like, what they're
24 comfortable with, what they're not comfortable with, and
25 really kind of engaging in a dialogue with consumers.

1 get people to react to is what kind of regulation do you
2 think will both allow the innovation and the potential
3 benefits of using information to go forward and also will
4 lead to benefits flowing back to consumers?

5 So, maybe everybody can go down and react.

6 MS. GLUECK: Well, now I wish I had put
7 in the slide about our cashback program. If you click on
8 the ad, you can get some cash back. But I think it's
9 worth looking at an EU style national privacy law.
10 Companies -- you know, a lot of companies are already
11 living up to those obligations because they're not just
12 U.S. companies. They do business all over the world.
13 So, the additional compliance cost for companies are
14 likely not to be significant.

15 I think that really the important thing,
16 regardless of what happens, to the extent there is
17 regulation, that it's done very thoughtfully and
18 carefully because I was fascinated by your work and the
19 effects you saw, unwittingly, you know, and it -- I
20 actually have a lot of questions for you about is there
21 such a thing as a beneficial state privacy health law
22 that could actually promote data sharing and, at the same
23 time, not reveal when celebrities go into rehab.

24 MS. MILLER: So, what I can say from our
25 research on privacy laws relating to healthcare, there is

1 substantial variation in the state privacy laws. We
2 actually don't know or we've sort of tried a little bit
3 to see if we can identify dimensions that were more
4 helpful or less harmful, and we didn't in terms of
5 variation between the state laws. That's something that
6 we're definitely interested in for future work.

7 But, right now, what I can say is that there is
8 a federal law, there's a privacy rule as part of HIPAA
9 that went into effect in 2003 and we don't find any
10 detectable effects of the HIPAA regulation coming as a
11 play. So, everything we're finding seems to be about
12 these state laws that are above the federal law. Part of
13 that, there could be -- certainly privacy advocates have
14 certainly said that HIPAA's privacy rule is very weak and
15 maybe that's why we're not seeing bad effects. So, maybe
16 there's a trade-off between having a law that really
17 works. But I think that there are other elements of the
18 privacy rule in HIPAA that might be useful for states to
19 think about. When they're thinking about setting their
20 rules that are stricter, maybe looking at those
21 dimensions in particular and maybe scaling back in those
22 ways.

23 MR. CHAVEZ: So, I agree with the point about
24 smart and careful regulation. But I will say that there
25 actually is a significant amount of competition in the

1 area of privacy. So, Microsoft, Yahoo!, Google, many
2 other companies have been competing in the area of data
3 retention, for example. You know, they talked about logs
4 retention. Microsoft has launched Internet Explorer 8
5 which has some very interesting privacy features.

6 By the way, is this --

7 MS. ATHEY: They're recording, actually, so
8 they want --

9 MR. CHAVEZ: Oh, are they? Sorry, recorders.
10 Hey, where was my privacy notice?

11 ( .)

12 MR. CHAVEZ: In private browsing in IE8.
13 Chrome, likewise, has an incognito mode. So, there is
14 actually a tremendous amount of activity at this point, I
15 mean, frankly, you know, in a lot of ways. I hear this a
16 little bit, I think, from the FTC and I see this in the
17 FTC's privacy principles is that, you know, proceed with
18 caution in the area of legislation because there really
19 is a lot of thought, for example, being given to this
20 notion of a value proposition for consumers when, again,
21 the thought of maybe something like a discount on a
22 product, if you're going to be placed into a particular
23 category, you know, sports lover.

24 So, there is just a lot of stuff going on. I
25 guess I would just say that it's worth monitoring and

1 looking at and making sure that companies are really kind
2 of living up to the promise that I think that we've
3 presented here. But we should be careful.

4 MR. ACQUISTI: Well, the way I would slightly
5 reframe the question is whether privacy can be a
6 competitive advantage for firms. So, whether selling
7 privacy can become a -- rather than just getting data,
8 can become a source of differentiation, as product
9 differentiation and practice differentiation.

10 The evidence I brought up earlier would suggest
11 that, no, because people -- in the trade-off between
12 privacy and money, they go for money. But we have other
13 results that show, in fact, that under certain
14 conditions, certain conditions, people will pay for
15 privacy. The conditions are you need to show very
16 clearly what the consequences of better regulation would
17 be. The privacy alternative should be very easily
18 accessible. So, you reduce transaction costs, cognitive
19 costs and so forth.

20 In that case, people react to privacy as a form
21 of feature that drives their choice of company, which
22 means that, to me, because these conditions don't always
23 happen frequently in many markets, a co-regulative
24 approach is the best, one in which there is a basic
25 background of legislation which protects some rights

1 which cannot be transacted away. After that, the market
2 can, indeed, allow for people to give away their data and
3 so forth.

4 MS. ATHEY: So, just one last comment on the
5 paternalism point. I guess I would just pause before
6 saying that we need to paternalistically protect people's
7 privacy because, after all, for your average person who's
8 not a celebrity and not a politician, in fact, what are
9 the objective risks to them from having this data shared.
10 They're fairly small and, in fact, you know, for most
11 people, getting a discount on their Internet service or a
12 coupon on the product is objectively worth more than
13 whatever financial risk anyways they would be subjected
14 to from the privacy. Again, the prevalence of medical
15 identity theft is very, very small. So, you know, if we
16 were going to be -- I would be very cautious to
17 regulators about trying to paternalistically protect
18 people against something that's not really a significant
19 risk, even as we need to make sure that some basic, basic
20 principles are upheld.

21 MR. ACQUISTI: So, maybe I was unclear because
22 I wasn't necessarily advocating paternalism, but at most
23 something which people call self-paternalism, which is
24 considering cognitive biases and not making a decision
25 for the user, but putting the user in the condition to

1 access rights for patients to be able to see records and
2 to challenge mistakes and correct the record. But this
3 express consent, this authorized consent, every time the
4 information is shared seems like a potential target. And
5 then some of the rules don't necessarily say explicitly
6 every time you use it, you need a consent, but they're
7 kind of open or vague on that.

8 I think one of the dangers and one of the
9 complaints that certainly has come up in the industry
10 about these privacy rules is that there's a lot of
11 uncertainty about what exactly is covered. So, there's
12 sort of a fear of liability where hospitals may not even
13 -- it may not even endanger them. You know, they may not
14 be coming up against actual privacy laws, but some of the
15 laws get worked out through cases and people don't want
16 to be the case that gets settled for multi-million
17 dollars to figure out that you broke the law.

18 And the other complaint is about a patchwork.
19 So, some of these hospitals are parts of systems that
20 span multiple states. So, there can be a cost associated
21 with trying to accommodate or trying to comply with
22 different laws in different states. So, that's another
23 area of sort of low-hanging fruit where maybe there's
24 benefits to coordination.

25 MS. ATHEY: Other questions? Scott?

1 MR. STERN: So, maybe this actually builds a
2 bit on Amalia's -- what are the regulations. But the
3 general question I had was, you know, if I thought about
4 the phenomena of privacy and, you know, people talked
5 about the Facebook generation, my sense is that a lot of
6 people -- and certainly anyone under the age of 30 --
7 sort of believes that Bessie has left the building,
8 right? That everything is out there, that there's a
9 tremendous amount of personal information out there
10 already and that closing the barn door at this point is
11 too late, so that the marginal returns they face from
12 doing anything active is extremely, extremely low.

13 In some sense -- so, I guess my question is --
14 I think the reason people believe that, and it was
15 alluded to, I think, in the HIPAA regulations where
16 everything is quite different than IT, is it would be
17 very difficult, I guess for me -- I hadn't -- when I've
18 thought about it, to figure out what people know about me
19 or the devices that I use. In other words, how do I know
20 what information Google has about me, not in principle

1 so much uncertainty about the level, they're completely
2 inconsistent in their preferences about the margin. I
3 guess that just seems to me the kind of -- you know, you
4 could imagine that policy would be very usefully
5 constructed that would, for example, give people kind of
6 an audit, you know, that would say, not just any one
7 company in particular. This is not a private company
8 thing, it's a policy issue. But as best as we can tell,
9 here's what people know about you.

10 MR. CHAVEZ: It's fascinating. It's like one
11 of the core questions. I'll just point out kind of a
12 difficulty and potentially something that I might
13 characterize as an irony of this.

14 So, in order for you -- so, for example, if you
15 were to sign up for a Google account, there's this
16 option, it's called web history, where you can actually
17 keep track of the searches that you've done and you can
18 pause if, for example, you happen to be purchasing your
19 wife's birthday present and you don't want her to see, or
20 you can delete. And the challenge, though -- so, that is
21 a feature that basically gives you access rights and
22 correction rights. But you actually end up knowing a
23 little bit more about you. So, you actually have to log
24 in. You actually have to identify yourself to us.

25 AUDIENCE MEMBER: (Off microphone) (Inaudible)

1 even if I do everything that Google (inaudible) I still
2 feel like, boy (inaudible).

3 MR. CHAVEZ: Like the big picture?

4 AUDIENCE MEMBER: (Off microphone) My sense is
5 that people have a very (inaudible) notion. In fact, I
6 think (inaudible). (Inaudible) people have (inaudible)
7 because they believe that the information out there about
8 that (inaudible) whatever. It's actually much, much
9 bigger than it actually (inaudible). In fact, as we saw
10 (inaudible) very limited information for a limited amount
11 of time (inaudible) with respect to the individual. But,
12 in fact, people believe (inaudible) do you think that,
13 you know (inaudible) knows everything you're doing?
14 Basically, 85 percent of the people would (inaudible) yes
15 and they're checking it all the time.

16 (.)

17 MS. MILLER: But they might be worried about
18 the government knowing everything they're doing, too.

19 AUDIENCE MEMBER: (Off microphone) I guess what
20 I'm saying is (inaudible) somehow (inaudible). In other
21 words, do you (inaudible) that you essentially have
22 accessibility of how information about you can be used
23 (inaudible).

24 MR. ACQUISTI: If I may (inaudible) on this, I
25 think it's an absolutely crucial point. It's just not --

1 take a look at -- in the EU. Are people -- where people
2 have a right of access under the national privacy laws to
3 contact companies and say, hey, what data do you have
4 about me, and if it was provided, say, as part of a
5 registration experience, the company is legally obliged
6 to turn over that data. Are people actually doing that?
7 Are they requesting corrections or is it merely limited
8 to, you know, that occasionally you update your email
9 address when you get a new job because you want to
10 continue to receive the newsletter that you were enjoying
11 while at your old job?

12 It would be interesting to see, you know, has
13 that really proven to be an important right for
14 individuals or is no one exercising it at all?

15 AUDIENCE MEMBER: I was just going to comment
16 from another area. In the area of credit reporting where
17 today your credit report and the score that's implicit in
18 that credit report affects not only your ability to get
19 loans, but it also affects the price you pay for auto
20 insurance and the price you pay for homeowner's insurance

1 verify that this information that was now quite valuable
2 and collected in a very central place could be verified.

3 The thought of every Internet company that
4 collects data based on cookies having some kind of
5 reporting obligation, I'm going to make you write that
6 rule.

7 () .)

8 AUDIENCE MEMBER: And control the costs.

9 MS. GLUECK: You couldn't authenticate the
10 users in that just based on a cookie ID. You'd only know
11 that it was that -- probably that particular machine.
12 But --

13 AUDIENCE MEMBER: Assuming it hadn't been
14 hijacked by somebody else.

1 AUDIENCE MEMBER: Yeah. I mean, it's a much
2 simpler problem because there were three companies that
3 were the core credit reporting agencies and everybody
4 consolidated around those companies.

5 MS. ATHEY: All right, we should probably wrap
6 up, so thanks very much, everyone.

7 (A . .)

8 (D 1 . .)

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