Seventeenth Annual Microeconomics Conference | FTC | November 14, 2024

Viola Chen:

Good morning. Good morning. My name's Viola Chen and I'm one of the staff economists here at the FTC. I am also one of the conference organizers along with Sam Kleiner. Welcome everyone to the 17th Annual FTC Microeconomics Conference.

So how many of you took an airplane to get here? Quite a few of you. And so you know at the beginning, before you go on your flight, they have this safety briefing for everyone that you're supposed to pay attention to, but you really don't. I have the pleasure of doing a similar sort of thing, but I do hope that you pay attention, because there will be a quiz at the end and it will count for 50% of your final grade.

One, please silence your mobile devices and any other electronic devices. Two, if you leave this building for any reason, you will have to go back through security. It does not take as long as the airport security, but it will take longer than you think it does. If there is an emergency that requires us to remain in the building, there will be instructions provided over the PA system. If there's an emergency that requires us to evacuate the building, we'll need to exit through the Seventh Street exit, turn left, cross East Street to the FTC assembly area. That's where the church is, and we'll remain there until we have clearance to return to the building again.

For visitors, when you came through security, you got a plastic FTC visitors badge. We reuse these badges for multiple events, so if you could please return those to the security desk at the end of the day, that'd be greatly appreciated. And also for our name tags, which you all experienced the wonderful snafu we had in the morning, if you could return the plastic badges to the registration desk, that'd be great as well.

If you notice any suspicious activity, please alert building security. Please be advised that this event is being photographed, recorded, webcast. By participating in this event, you are agreeing that your image and anything that you say may be posted indefinitely on the FTC website and on any one of the Commission social media sites. The restrooms are behind me. Women's on that side, men's on that one. There's also a coatroom next to the men's room, which I find to be useful, but just don't forget your stuff. Wifi is available. The instructions are at the registration desk. We do have our conference-sponsored coffee and food over in that corner, but if for whatever reason it's not to your tastes, we do have a cafeteria here. And new this year we have a charging station, so we have extra outlets in the back over there. That is thanks to our FTC event staff.

Okay, so got through that and now we can actually begin our conference. I have the honor of introducing our Bureau Director, Aviv Nevo. We are very grateful for his leadership here at the FTC as he's currently on leave from the University of Pennsylvania where he is the George A. Weiss and Lydia Bravo Weiss PIK professor with appointments in the Wharton School and Economics Department. I give you Aviv.

Aviv Nevo:

Thank you, Viola, for doing a great job with the safety instruction and for getting through my title, which I never can. So, thank you. So as Viola said, my name is Aviv Nevo. I'm the Director of the Bureau of Economics here at the Federal Trade Commission. I would like to welcome you all to the 17th Annual Microeconomic Conference hosted by the FTC. Personally, it's a great pleasure for me to be here.

I was actually on a panel on the very first conference in 2008 that was actually held at the New Jersey Avenue location. I think there's some folks here who might remember that location, but most of you probably don't even know where it was, and I was on the Scientific Committee of the next three conferences after that. So it's really a true pleasure to see this conference be as successful as it is and really sort of continue. Actually, as a side note, I think we've liked this conference so much that we started another one, more of a marketing conference. We had the second annual one just a few weeks ago, and we're going to continue on having it kind of on a spring schedule from year to year.

From those of you from outside the FTC, I want to say a few words about our agency and the Bureau of Economics or BE as we like to refer to it. As you probably know, the FTC is an independent agency and it has two primary enforcement missions. Consumer protection and competition. BE supports these two missions. We have just under 120 FTEs with roughly 95 of them PhD economists, many of them which are here in the audience and you'll get to meet today. That makes us one of the larger groups of microeconomic economists in the federal government and we do a lot for the agency. We support the competition and consumer enforcement missions. We provide economic analysis in support of investigation and litigation, and we apply in many cases cutting-edge economic analysis, both theoretical and empirical.

I've been very fortunate to have the opportunity to work with the BE folks and the FTC staff more broadly over the past two years. At some point, hopefully many years from now, when I look back at my career, serving as a BE director will surely be a highlight. For the young and maybe not so young folks in the audience, if an opportunity to serve at the FTC or for that matter, our sister agency, the DOJ, ever presents itself, my advice is to take it. If someone offers a job, take it. It's a great job. This is truly a unique experience and one that I highly recommend to anyone to do if they have the chance.

The last few years have been a particularly exciting time at the FTC. We've had a lot of interesting things going on and BE is right in the middle of the action. One of the many ways that BE contributes to the agency is by bringing knowledge from the academic community into our work. Interactions with the academic community, like at this conference that combines cutting-edge academic research and discussions of real-world policy problem is key to achieving this goal. You might not realize it, but your research can have a real impact on both policy and litigation outcomes. I would like to take a few minutes about a couple of issues that stand in the way of research achieving its full potential impact in this way. Let me stress that the views I'm about to express are my own and do not necessarily reflect the views of the Commission, any individual commissioner or that of the FTC staff.

So of the two issue I want to raise, the first one is we, the FTC and BE, value an open exchange of ideas between the staff and experts outside the agency. This enables the staff to learn about new ideas and perspectives, hone the professional skills and receive feedback on their work. However, such a dialogue requires transparency with respect to relationship with interested parties so that there's no question whether undisclosed relationships may have extracted influence on the opinions expressed. The profession has come a long way with disclosure requirements set, for example, by either the AEA or the NBR, but we still have a ways to go. I've been to many conferences where presenters do not offer disclosures or make some vague statements such as reference to a webpage. Okay, you want to see my disclosure, it's on my webpage that you can go look at later, but the audience can't see in real time and can't make judgment in real time about the opinions being expressed.

Now in part, I think this is due to lack of clear standards. At times, folks do not know what is expected to be disclosed in oral presentations. For this reason, I would like to share with you today that BE has a new disclosure policy that we're about to introduce and that we will enforce from now on in our conferences and seminars. And frankly, I hope that the rest of the profession follows it or some version very close to it as well. The policy is a modified version of the AEA Journal Disclosure Policy. For example, we clarify the center funding, not just personal funding needs to be disclosed as well as funding received potentially by a spouse. So that's one of the things that need to be disclosed. We clarify that there's no expiration date for disclosure of matters where the presenter or a co-author was directly involved. For example, if someone worked on the Microsoft conduct case, they are expected to disclose that if they're about to talk about the case, regardless of how many years have passed since.

Finally, we clarify how disclosure is expected to happen in talks or panels as opposed to written paper submissions. The AEA Journal Policy talks about submissions. Here we sort of say, if you're on a panel, what is it you're expected to say? We will be posting the new policy very soon, so please keep an eye out for it. It's a bit too late to ask everyone in this conference to follow the exact letter of the policy, although I hope that you will follow the spirit of it. Okay, a good rule of thumb, if in doubt, please disclose. And if you have nothing to disclose, please just say so. "I have nothing to disclose." It's really not rocket science.

The second issue I'd like to discuss is a bit more delicate. It involves our credibility as a profession and how it is being eroded by questionable testimony. As you probably know, the FTC has been very busy with litigation. We litigated two mergers earlier this fall, a supermarket merger litigated in Oregon and a handbag merger litigated in New York, which by the way, just this morning, the parties announced that they're abandoning. And we're in the middle of litigation in Houston. Literally, the case started two days ago. Unfortunately, some of the arguments that I've heard from defendants, economic experts doing these cases and more generally literally make me cringe. Let me briefly mention a couple of examples I saw during my time at the FTC.

In a recent decision, the judge was quite critical of the defendant's IO expert, at one point saying that the statistics cited by the defendant were "deficient and ultimately misleading." This is a direct quote from the decision. And at another point saying that the expert "was unable to adequately explain the discrepancies in the reseller data". And therefore the court found the testimony "unreliable". Now, frankly, this kind of language is not uncommon. Ultimately in cases, one side loses and a lot of time you get language like that for one of the experts. But the specific details in this case are not common and, frankly, quite outrageous.

For example, at one point the expert presented a table claiming to show that a product doubled over the span of a few years. It turns out that a key outlet was missing from the data in the first year and that its "introduction" as if it sort of came into, was introduced, which was presented as an entry. So it was really missing data, but was presented if, look, this outlet sort of entered was a major driver of the increase, which of course totally undermines the point of it being an increase. Really it was just a data issue.

This was not the only example. The lack of rigor was systematic and disturbing and I don't have the time or some of it's not public, so I can't go through all of it. But this was especially troubling since the expert in the own testimony criticized the FTC's expert analysis as "not up to the standard" and that the evidence, again, "is not at the level of rigor that I would expect." I personally strongly disagree with this assessment. The industry in question does not have data, for example, claims data in healthcare that we all know and sort of work with or scanner data in consumer packaged goods, but the FTC team and its expert did an excellent job using the available quantitative and qualitative evidence to support its case. In this case, well, this case given where it is currently, I can't go into more details, but I would have no problem standing in front of you and literally presenting the whole evidence and proudly defending it. Again, there's some assumptions you need to make, but proudly defend it. Sadly, this example is not the worst of it.

In another example, an expert testified that when considering pricing, a joint owner of two brands would not, and again, I quote here, "actually want to get involved in trying to coordinate them." You take two brands, you put them together and an economic expert got on the stand and said, "From an economic point of view, you don't necessarily want to coordinate them." This was not made as an empirical observation. There was no nuance or specificity to this case. It was made as a general theoretical argument. In my opinion, this is an extreme view that undermines the basic economic principles underpinning horizontal merger enforcement, namely that incentives, pricing and otherwise change under joint ownership. Frankly, as an editor or as a referee, I would've found this type of statement quite troubling. Again, unless it had some sort of specificity or nuance to explain what it is, which was not here. I would've find it quite troubling and obviously acted accordingly. Now, you might be tempted to brush off this and say, "Look, folks say crazy stuff all the time, that's the cost of doing business." That would be a mistake. Stated like this matter for two reasons. First, the above examples did not impact the ultimate decision, but the outcome could have been different. The court could have been confused and could have created bad case law that would've hurt enforcement throughout. Second, the credibility of the expert has taken a hit. Folks would sort of notice this type of statement. But this sort of repeated behavior from numerous actors hurts us all. We are slowly but surely eroding our credibility or losing credibility as a profession.

So what can we do about it? So I would say two things. First, individually, we should be more responsible. Again, let me offer a very simple rule of thumb. If you are not willing to stand up in the front of a room full of economists like this conference and repeat and defend what you said in court, then maybe you should not have said it in the first place. Not something too sophisticated. That's kind of I think a simple rule of thumb, and I would say that many cases' testimony would probably fail that.

The second thing is collectively we can do more as a profession. It's time to call out these questionable testimonies when we hear it. What happens in the courtroom should not stay in the courtroom, unlike Vegas. The testimony is public and we should call out folks on the outrageous claims that they make. Our profession does not have a process equivalent to removing someone from the bar that the lawyers have, but hopefully professional reputation still matters, and if we call people out, hopefully it will create some sort of incentive to eliminate the really crazy stuff. So as you can tell, or maybe not, I'm quite passionate about this topic and, frankly, I could probably go on for a while, but I think it's time to move on to the conference.

This conference will not be possible without a long list of people working behind the scenes. So I'd like to thank Steve Berry. Where's Steve? I think I saw... There he is. Thank you, Steve. And the Yale Tobin Center for co-sponsoring the event. I'd like to thank the conference organizers, Viola, Sam, Stephanie. Where's Stephanie? You'll see her during the day. All from BE and the Scientific Committee. Allan Collard-Wexler from Duke, Zack Cooper from Yale, and my pen colleague, Pinar Yildirim. Special thanks to our admin team here at BE, Maria, Kevin, Constance, and Tammy. And to the research analysts and statisticians that helped with the registration, Aidan, Jules, Chris, Jen, Dania, and Chris. Last but not least, the FTC media team and the event planning team and the numerous BE economists who helped screen the great submissions and work with the Scientific Committee. So with that, I'd like to turn it over to Sam, who will introduce our first presenter. Thank you.

Sam Kleiner:

All right, thank you very much, Aviv. So to kick off this first session, we have Yanyou Chen from the University of Toronto presenting, Driving the Drivers: Algorithmic Assignment in Ride-Hailing. And that paper will be discussed by Nick Buchholz from Princeton University.

Yanyou Chen:

Okay, should I get started? Okay, cool. Thank you very much for having me. So I'm Yanyou Chen from University of Toronto, and this is a joint project with my colleague Yao and University of Toronto and Zhe Yuan from Zhejiang University. Following Aviv's instructions on disclosure, this project is funded by the SSHRC in Canada, so Social Science and Humanities Research grant, and I have nothing else to disclose. Okay, so I will present Driving the Drivers: Algorithmic Assignment in Ride-Hailing.

Recent years, we have witnessed this advancement in algorithmic technologies. While the existing literature has focused mostly on pricing algorithms, especially how algorithmic pricing is going to lead to market outcomes such as collusion, there has been less attention on non-pricing algorithms, which the platforms also use to, say, shape the worker behavior. One prominent example of those non-pricing algorithms is actually assignment algorithms, which are widely used by gig platforms, including ride-hailing, food delivery, and parcel delivery services. How those algorithms work is usually the platform will assign a score to a particular worker based on the worker's historical performance, and the workers with higher score will receive better or more other assignments from the algorithm. While those systems are designed to optimize efficiency, but they can on the other hand also limit the flexibility and autonomy of the workers. This brings us to our project. So we provide the first empirical study of such a preferential assignment algorithm and we examine what are the impact of those algorithms on like labor behavior and their welfare. Our research centers around two research questions. First, we want to know, do those algorithms actually favor some workers? If so, why and how do they do that? Secondly, we want to evaluate if the platforms are no longer allowed to do those preferential assignment algorithms, what will be the impact for their labor welfare and also for the platform revenue?

Here is a very quick preview of our findings. Our reduced form evidence suggests that the preferential assignment algorithm is closely tied to the hourly work schedule of drivers, and we found drivers favored by the algorithm earn on average 8% more than those non-favored drivers. Next, our structural model results suggest that if we eliminate this preferential assignment algorithm, it will have very substantial effects. The platform revenue on one hand will reduce by 12%, and on the other hand, drivers, especially younger and local ones are going to benefit. They will see this increase of their welfare without the algorithm. Our research ties to several literature. First, we speak to the current literature on how algorithms influence market outcomes, and our paper contributes by focusing on non-pricing algorithms, and we empirically examine what are the welfare impacts of those non-pricing algorithms. Secondly, we also build on the labor literature, especially those on compensation and the work flexibility. Third, we contribute to the growing literature also by the discussions and some of the audiences here. So on the growing literature on taxi and ride-hailing, and we utilize IO techniques to study the counterfactual scenario of if we eliminate those preferential assignment algorithms, what happens to the social welfare?

Let me now provide you a little bit more details for this particular preferential assignment algorithm we study in our paper. Here is how it works. Once the order is initiated for the ride-hailing platform, the algorithm will decide whom to allocate to the order. There will be some available drivers nearby this initiated order and assume there are two drivers there. So the higher score drivers will get priority and receive the order. Sometimes the algorithm will even prioritize the high score driver even he's a little bit further away from the consumer. That's how this preferential assignment works.

And then how does this score system work? This is a generic representation of what the driver actually see on the screen of their app. So first they see their score in this case is 236. The score comes from completing orders for the platform. So for each order they finish, on average they get 0.3 points. The total points here is calculated and the summation over the past 30 days. So it's a rolling base based on the past 30 days. And then the drivers are told their percentile ranking given their score. In this case, there is a line below this, 236 is better than 66% of drivers in the same city. And also, there is a sentence literally saying the higher the score, the higher priority you'll get in other assignment. So in summary, the drivers, they know exactly what their score is, they know how the score is calculated, and then they know their percentile ranking and they know what the score is used for.

Another thing I want to emphasize here is on average the driver receives 0.3 points per order, but there are specified incentivized hours. So, say, maybe the afternoon peak hours are incentivized. During incentivized hours, the drivers will receive more points by finishing the orders. So I hope that clarifies on how this score system works and, as I said earlier, different gig platforms use a very similar but a little bit different scoring system for the workers, and the preferential assignment is based on those scores of the workers.

Then the natural question or the first question would be why do this? So we all know the search pricing and all those wage discrimination the platform could use. So why use preferential assignment algorithm? We try to provide a very simple theory or some toy explanation for why such preferential assignment exists. First, in this particular case, if the platform can use perfect wage discrimination and extract all the consumer and driver surplus, then preferential assignment algorithm has no effect at all. So that's the first degree, first best the platform can achieve.

But in reality, it's almost impossible for the platform to extract all the driver's surplus either because of the design of the wage scheme or because of some labor loss. So, for example, in France there is this requirement for minimum payment for each ride, which will give you this minimum wage. In that case, then like the simple illustration here, so without loss of generality, we'll assume the drivers have zero outside option. So the red line at the bottom is a labor supply curve, and then we have the blue line to represent the labor demand. In this case, the equilibrium points, given the minimum wage requirement, we'll have only L8 drivers to be able to receive orders. The platform then has the authority to decide who will be those L* lucky guys to get the order. So this is really what gives the platform power to implement the preferential assignment algorithm.

So exactly how does this work? The intuition is that the platform communicates to the drivers saying, "Come and work more. I'm not going to pay you higher incentive wages, but I'm going to give you priority in other assignment." Then let's assume we'll have two time periods. So time period one is exactly what we said. They will have more supply than the market could clear, and then we have a second time period. In normal times, if you want to motivate drivers to work more, you need to pay those high incentive wages. So in this case, say time period T2, if we want to increase labor supply from L2 to L2 prime, you need this additional F2 plus F3 incentive payment.

But with a preferential assignment algorithm, the platform is essentially telling the drivers, "Come and work in time period T2. I'm not going to pay any additional incentive wages, but I will give you priority in time period T1. So you will be one of those lucky guys to receive order in that time period." Then what is happening here is that because of this imperfect wage discrimination, though, drivers will have some additional surplus and the preferential assignment algorithm can help the platform to further extract that particular surplus. So in summary, we will say in reality it is almost impossible for the platform to extract the entire driver surplus, so the preferential assignment algorithm is valuable for them. And another reason is that the prices and wages are nowadays very sensitive topics and they will receive scrutiny from federal agencies and also workers. In a recent case in Canada, the Uber drivers, they complained and had a protest over the new pricing scheme of Uber. And also, this is confirmed by our interviews with the drivers.

So based on our interview with them, we asked them what are their thoughts on, say, search pricing and the preferential assignment algorithm. Their perception is any types of wage differential, they think is unfair. So they should get paid exactly the same wage. But then we asked them, "Hey, what do you think about preferential assignment algorithm?" They think it's fair. The reason is because they think the more you work, then of course you should get higher priority. This boils down to our key insight of this particular paper. So those preferential assignment algorithms are widely used by the platform, and on the surface they may seem fair, but there comes with hidden costs and I will show in more details that they will limit the labor flexibility and autonomy and those often goes unnoticed by the workers themselves.

So given that, let's move to our empirical study to show exactly what is the welfare impacts of those preferential assignment algorithms. Our context is a very large ride-hailing platform in Asia, and we have all the completed and initiated the proposed but unmatched transactions in a given month of this major city in Asia. So we observe every attribute for the order, like the departure, destination, distance, price, so everything you can imagine for a particular order. On top of that, we also obtained driver attributes, demographics such as age, gender, and the birth location of the drivers. For our focal platform, in this particular market, the focal platform has over 90% of market share. So in our study we treat it as essentially a monopoly in this particular market. We understand the preferential assignment algorithm may have some competition implications, like you want the drivers to be loyal to your platform, but this doesn't directly apply to our case. So we abstract away from this competition effects.

Regarding the summary stats for the driver hour level, we aggregate everything to the hourly level so we can construct the hourly wage for the drivers. One thing I want to emphasize here is among each working hour, the driver only spends 30 minutes to serve the drivers, which is also confirmed by a study using Uber data. You can see the idle time is about 15 to 20 minutes. So it means this assignment is really important for the drivers to earn higher profit. First thing we want to examine is who earn higher hourly wages in this case. The platform tells the drivers how the score system works, but does this really result in any difference in the wage? So we want to confirm that. We show that if the drivers work more hours in a given month and their hourly wage or their hourly earnings will indeed be higher, especially if their percentage of working hours is during those incentivized hours. You can see the hourly wage, like earning is higher for them. So we control it for like this. So there is no search pricing for this particular platform. Therefore, you shouldn't worry about, hey, during incentivized hours, maybe per order you get paid more. It's not the case.

And here is how we think about the decisions of those drivers. During our studied time period, the incentivized hours are midday from 10 A.M. to 4 P.M. and from the evening hours from 7 P.M. all the way to next day. We think the decision of drivers and choosing either to be essentially the full-time worker or part-time worker. So if choosing to be full-time, they can commit to one of the 16 schedule, which means they work for at least two consecutive hours during the incentivized hours. That's a minimum requirement. So they fulfill that and then they can freely choose for other hours of working whether they want to work or not. And for the, we call it low-score drivers or non-committed drivers, they have full flexibility of choosing whether to work or not for each hour of the day.

And then we show some summary stats for who are those high-score drivers and who are those low-score drivers. We found 70% of the non-locals in this particular city, they have this residence permit, which you require to get some health benefit to buy houses. So we find for those non-locals, they are more likely to be high-score or full-time drivers. So this could be because they have limited outside option in this particular city. And there is no significant difference between the age and for gender. So we don't find significant difference as well. One thing special about this Asian market is we only have 5% of drivers to be female, which is very different from what we observe from Uber data, around 40% to be female. This could be-

Yanyou Chen:

40% to be female. Okay? This could be one of the consequences of having this preferential assignment algorithm because, usually, we may have female prefer those flexibility more, but will get penalized by the preferential assignment algorithms. Okay.

So then, we show for different hours of the day, do we see earning difference between the high score and low score drivers? So this is conditional on both those drivers working in a particular hour. We find this systematic, which differential between the high score and low score drivers. It's about 8% more. Okay.

So if both high and low score drivers are working and we will find the high score drivers will likely to have 8% more hourly earnings. Then, of course, I think here is the point where all kinds of indigeneity or decision comes into your mind. Maybe, those high score drivers will be more experienced, so they know where to find those drivers. And that's why they have higher hourly earnings. Okay.

So we will try to exclude all those competing hypotheses. First, we explain where this 8% additional hourly driving comes from. We find that the high score drivers, they indeed finish more orders, and they are matched with better consumers. So they have consumers have lower cancellation rate, and they will spend less idle time waiting for the order to come. Okay.

And so in summary, they get assigned more rides and what the platform promised. And they spend less idle time, and they get assigned better orders. Then there definitely could be competing hypotheses. Especially from the literature, we know more experienced drivers. They are more likely to cancel orders.

So they are shopping around like, say, which order is better. So we are going to rule out three competing hypotheses, which is they strategically choose where to work. They strategically cancel orders, and they simply drive faster to finish more orders. We show this is not sufficient to explain this 8% more wage difference.

First for whether strategically the high score drivers strategically choose where to work, we have some simple test to show in the different districts of this particular city. We don't have statistically difference between where they work compared to low score drivers. But then, we want to do a more thorough examination for this.

So our thought experiment is that if you control for very fine grade, okay, so say exactly in the same location, you have two available drivers, one high score, one low score. Do we see the order goes to the high score drivers? So that's essentially this analysis we do here. So the short answer is yes. Even condition on the exact same location, same time of the day for two available drivers, the highest score drivers will receive more orders and hence earn higher hourly wages. Okay.

So that shows they are not strategically working at different locations. And secondly, we show those high score drivers more likely to cancel orders. This is opposite to what we found for the US Uber drivers. Actually, for high school drivers, they have a much lower probability of canceling the order. One reason could be they get assigned better orders. Okay. So they have lower cancellation rate, but this shows they are not strategically shopping around to cherry-picking the best orders.

Indeed, the high score drivers drive a little bit faster, but this only explains for 0.5% of this wage differential. So the large amount is still explained by the more number of orders the high score drivers get assigned.

So from here, we hope that we rule out some of the concerns for the drivers. They strategically choose where to work, strategically cancel orders, and simply drive faster. Okay.

After establishing that, we want to know, back to our original question, what is the effect of this preferential assignment algorithm? So if we eliminate this, who will benefit and how large will be the labor welfare become? In order to do that, we build a model of this dynamic labor supply decisions. So drivers will choose whether they want to be high score drivers or low score drivers. And then they decide for each hour of the day whether they want to work like each hour of the day, whether they work or not. Okay.

So for the high and low score drivers, their wage composition comes from first the platform charges 20% of the commission. So it's fixed. The platform doesn't do any wage discrimination. This is also confirmed by our interview because the drivers really hate that. They don't want any wage discrepancy.

So the wage depends on the commission rate, and then this assignment, ST, depending on the platform, decides how much orders they are going to assign to high score drivers compared to low score drivers. Okay. And also this will be effect by this congestion effect like how many drivers are available in each particular hour of the day.

So the workers' schedule for the high school drivers, they can commit to one of those 16 schedules I showed earlier. So they first commit to this schedule and then condition on that for each hour of the day, they decide whether they want to work or not. And for those low score or part-time workers, they can choose freely what they want to do. And then given these choice decisions, then we can construct this aggregate labor supply for each hour of the day. For labor demand, because the price is fixed for each hour of the day, there is no surge pricing.

So we have the fixed elasticity given the constant elasticity of demand. And then given the driver labor supply decision, the platform will choose how to allocate the orders. So essentially, how discriminate they want to be in order assignment. And then here is this... Driver's decision for each hour of the day, the driver essentially choose whether they want to work, which they will get the wage or not. So they will get outside options.

Then, of course, as you can imagine, there will be selection issues. So some people have lower reservation values. They are more likely to be, say, full-time drivers. And some have high reservation values and different hours of the day. So they are more likely to be part-time drivers. Okay. We control for that using this unobserved heterogeneity. So we allow each drivers to have unobserved type, which will affect their decisions to be the high score or low score drivers.

Given that, we also assume there is a starting cost. We call it warm-up cost. This is also from our interview and our institutional knowledge, knowing that it takes efforts and takes some fixed cost for drivers to start working. Okay. So they will incur this kappa warm-up cost.

All those will translate into this aggregate labor supply decisions. For our estimation, we use the conditional choice probability to estimate all our parameters, so which is hourly reservation value and then this heterogeneous type data for different types of drivers. We also estimate the warm-up cost kappa and the normalization term for the standard for the extreme value type errors.

We estimate through this minimize observed conditional choice probability from the model predicted choice probability. Here is what we observed from the data. So first, we know who are the high score drivers, who are the low score drivers. And we know their decisions of in the last hour whether they have worked or not and condition on that. What's their decisions on working? Okay.

So here, you can already see this effect of the high warming up cost. So for the red line, it's the high score drivers. For the blue line, those are the low score drivers. And the solid line means they have worked in the past hour. Okay. So conditional, and they have worked in the last hour, their probability of continuous work is much higher than if they didn't work in the last hour.

Here is our model feed for all those four results. So given the number of parameters we have, we will say we did a good job in feeding the data. The place where we are mismatched is during the early morning hours, like from the 12 AM all the way to six AM. One reason is because you have much fewer transactions during that time period. So that gives us less fitness in that time. Okay.

Our first results for the reservation values, this is the average reservation value for the 24 hours of the day. You can notice during the morning and afternoon peak hours, actually, the drivers, they have lower reservation values, which is very intuitive. But during the midday and especially during the early morning, they have high reservation values. This is one of the reason to explain why the platform wants to give this incentivized our scores for this midday. Okay.

And then for our unobserved heterogeneity, so the platform has six schedules, and we allow there to be a different outside option value for all those six schedules. We estimated our unobserved heterogeneity, and we find this so-called group three, group two and group four to have the highest population density.

So what does this mean? If you look at group two and group four, those are the ones in the bottom. So during midday and early night, they have low reservation values. So those groups are likely to be low score or full-time drivers, because they have low reservation values. For the other type group three which have very high reservation value during the late evening, those are likely to be part-time drivers. So we can think about they need to pick up the keys during that time so they have very high reservation values.

Then we map this into observed demographics. We find group two and four are more likely to be older and non-local drivers. And for group three, they are more likely to be younger, local, and male drivers. This will give us interpretations for this distributional effect when we talk about elimination of preferential algorithms.

So our main counterfactual is studying. If we eliminate this preferential algorithm, now, we do a fair random assignment essentially. So whoever is available, we will do this random assignment, and we will see how the welfare changes.

First, I want to show you how the platform are leveraging the differentials between cross-time labor supply elasticity. What I mean is that if you look in the left panel, panel A, this is a labor shortage if we remove the preferential assignment algorithm. You'll see a huge labor shortage during midday around 12 to two PM. given their high reservation value.

But if you look at the wage differential calculated, they don't pay much during the midday. Instead, they pay wage differential during morning peak hours, and the night peak hours. Okay. The reason is because maybe demand is more inelastic during those hours. So they are leveraging this differential in cross-time elasticity.

Then who gains and who loses from this eliminating preferential algorithms? We find first drivers, they do value flexibility quite a lot. So now, additional 10% drivers would switch to this flexible schedule without the preferential assignment algorithms. But platforms will have revenue decrease by 12% because now, if they want to incentivize workers to work, they have to pay those high incentive wages.

If we re-optimize the ride fare, we will see that the ride fare will increase by almost 8% without the preferential assignment algorithm. So essentially, the message here is that the platform is utilizing the preferential assignment algorithm to push drivers to work more hours. And as a customer, we do benefit from that, which means we don't need to pay high fees for them to work.

So the trade-off is really like platform and consumers versus drivers. So if we remove the preferential assignment algorithm, the drivers, they will have larger surplus, especially for those non-local and younger drivers. They are going to benefit from this elimination of preferential assignment algorithm.

In conclusion, we provide the first empirical study of this non-pricing algorithm, specifically the assignment algorithms. And we empirically analyze what are the welfare effects of those non-pricing algorithms. Okay. And yes, so that's end of my talk. Thank you very much.

Speaker 2:

Oh, this is the clicker. Okay, this one. Got it. Great. Thanks so much. It's a pleasure to be here. Thanks, Yanyou, for the great talk. So I want to start by just first saying this paper analyzes the ability for platforms to utilize new forms of control over markets in order to achieve its own objectives.

So this could be, for example, just making more higher profits, could leverage control over the way that workers in a gig economy platform match with consumers and studies kind of the equilibrium effects of this sort of new forms of control.

But it also raises many interesting questions, novel questions about the way that these levers can be used to generate and exploit market power, and this being the FTC. That's what I want to spend my remarks on. So what's different in a gig economy platform or a platform in general is that there's more than just the ability to distort P and Q.

Here, the platform can actually exercise more influence over exactly how matches get made. And so that's the space where these questions arise. So what's unique about that compared to these traditional forms of market power?

So here are some options or some possibilities that I want to consider. First is platforms collect immense amounts of data. So you can think of a labor market platform as repeatedly writing contracts with workers and offering different prices and seeing if workers choose to participate or not. They do the same thing on the consumer side. So they're amassing immense amount of data. What will they do with that data? Well, one thing they can do is use it to learn about the opportunity costs of workers or the willingness to sell their labor. Likewise, they can learn about on the consumer side willingness to pay for services. So this gives them the ability to engage in price discrimination.

In this paper, we're thinking about how the platform might leverage this information to offer different prices through this assignment mechanism at different times of day. So I might reward you for serving the market during a down hour with better assignments during a time of day that's more busy. You could also think of this price discrimination as operating across different workers too.

We might offer different assignment rules to different types of workers as we also see in this paper. Beyond price discrimination, we can also think about different ways to leverage network effects or lock-in order to improve the position of the platform. So an example of this would be offering kind of nonlinear rewards or convex reward schedules to drivers so that if you're a high-volume driver, you wind up participating and getting tiered bonuses. Let's say, Uber and Lyft might give you bonuses that increase with the number of rides you do in a week.

And in that circumstance when you're kind of a high volume driver, you're going to wind up with a reward schedule that makes the platform you're on more in a better competitive position than, say, start multi-homing and going to a competing platform.

Those are just various examples. And then, in Yanyou's paper, we're thinking about kind of a platform. This is a ride-hailing platform in Asia that institutes a policy which touches on all of these issues. So the platform is going to offer workers the ability to opt into a high volume schedule or not. And if you're on the high volume schedule, you're going to get these preferential assignments.

So here's a brief or radically condensed summary of the model that we can use to motivate this. Consumers have CES demand. They see the price in the market, and they come to the market. Consumers are sort of second order in the model. It's really about understanding the labor market side.

The platform then has a couple of choices to make. It chooses what price to set in the market. So it's going to set a price that is going to clear both on the consumer side and the worker side because workers are getting a fixed reimbursement from that price. And the platform also chooses an assignment rule S. So that's the unique piece here. The assignment rule says what share of rides that show up will I assign to the kind of high preference workers versus the low preference workers? So those are the two major levers. And now, let's think about what this does, how this transforms into a wage rate. So here's kind of a rewriting terms of the model. So wages are going to arise from consumers arriving to the market. This is Q coming from the demand curve times the probability that any consumer is assigned to any driver.

So that's going to be a combination of the likelihood that a chosen consumer gets assigned to a high type driver or low type driver as well as the total number of drivers in the market. So S divided by N. So that's the likelihood of any driver meeting one consumer. And what do they get when they serve their ride? They're going to get the reimbursed share of the price. So this is P times one minus R. And this is going to be an 80% of the ride price.

Okay. Now, the model has a lot more to it. I am simplifying this. So when we offer kind of different wage schedules to drivers, they're going to accept or not accept, and the platform will see that over time and be able to learn about the underlying opportunity cost of drivers. And that becomes the basis for learning how to set these assignment rules optimally because we're going to set them such that we get the employment schedule that we want as the platform. Okay. So the paper's going to look at what's happening in the status quo. They have these assignment rules. It's going to compare that with a world in which they just have uniform assignment rules. So what's the effect of this assignment rule in equilibrium? I think the quantification here gives very credible kind of believable effects, which is that naturally the platform, when you give it one more degree of freedom in pricing, it's going to do a bit better. And we see that come through. It's going to be ultimately worse for drivers overall, and it leads to the ability to lower prices slightly. Okay.

So that's I think a very credible and believable result. Now, what I want to talk about is that this is what the platform's doing. And so from that perspective, I We're showing in the paper that the platform's policy is working and here's why it's working.

However, if we rewrite the terms of the wage equation, drivers are earning as their wage rate. There's no fixed wage. It's just coming from the flow of trips times the reimbursement rates. So drivers are getting some reimbursed part of total trip revenues times the probability that, that trip revenue flows to them versus a different driver. So one minus R times S is what they're getting in the status quo.

And notice that through the lens of the model, you could just rewrite this to put the lever instead of on S, let's fix the assignment share and instead put all of the variation on the reimbursement rates. So one minus RT. If we transform the model to just operate through reimbursement rates, which is actually just the price facing the driver. Then, the platform, you can think of this as just these two things as isomorphic, the platform could just offer specialized assignment, or it could offer customized reimbursement rates, which is just kind of conventional price discrimination.

Now, we know in the data, they are doing the version where they're controlling assignment and not the reimbursement rate, which is why I think the numbers we're getting makes sense. That's what the platform's doing. But this raises the question, why? Why don't they instead just choose to operate on the driver facing-prices instead of assignments? Yanyou gave some good reasons for this. It may just be a sense of fairness among drivers. It may be that there are regulatory constraints.

Here's some other potential issues to consider. The platform may want to keep the price signal to itself and not offer drivers a chance to see how much they value their trips. So the assignment rules are going to be opaque. And so we can think of reasons why that might be better, keep that information in the hands of the platform.

Second, they might introduce a stronger intertemporal commitment in the sense that if I assign you a series of trips during a busy time when you're likely to quit, if I keep you busy, then I'm also keeping the drivers from facing the decision point. Do I want to stop now or not? So you could think of the assignment rules as imposing this kind of intertemporal commitment by giving them less down periods. And finally, they may be able to use these assignment rules to control match quality, which is kind of a set of features missing here.

For example, a trivial example, maybe I want to match high-type drivers with high-type riders, a five-star driver or the five-star rider. And we could think about reasons why that might be beneficial. I know I'm out of time. So I'll just conclude by saying this opens a kind of whole new area where we could think about the role of match quality.

Match quality can take many different forms on the driver's side. We can think of it like getting a match to somewhere near where I live so I don't have to take a long trip to drive home. On the customer's side, we can think of match quality as offering lower waiting times or just something like waiting on both sides. So if we imagine an enhanced version of the model with match quality, this gives new ways to clear markets on both the straight pricing dimension or on this kind of quality dimension. And then the question becomes why would the platform pick between different ways to clear markets? And thinking along those lines might give us insights for understanding why platforms would choose assignment rules over just direct price discrimination. I'll stop there. Thanks very much.

Speaker 1:

Okay. I think we have time for maybe a couple questions.

Ginger:

Thank you. Very nice paper. I have two comments. One is my first reaction to this is seems like a reputation system. If you're thinking the drivers differ in their service quality commitment to serve or other things, if we're thinking it that way, how would that change your sauce on the paper? My second comment is if this motivates the drivers to commit to long-time driving, to what extent that may generate side effects like driver fatigue or traffic problems and other externalities to the public?

Yanyou Chen:

Indeed. So, Ginger, thank you very much for the question. So first, regarding does this change driver behavior? I would say yes. The reason is because in our data, the average, the mean working hour is about seven to eight hours. But if you look at Uber data is about four hours only. So we do believe this drives them to work more extended hours.

And this may answer to part of your first question, is this really just reputation? We don't think so. We think the intertemporal commitment point Nick raised is very important here. This do force them to work more extended hours. And just also maybe to answer Nick's question on this service quality, we thought about this like, hey, you get 4.9 star or five star for drivers. Does platform care about their ratings?

For ride-hailing platforms, less, because if you pay attention to your Uber drivers, the average is like 4.8, 4.9, so there is very little variation on that. But for my other project with the food delivery platform, for food delivery, service quality is very important because I don't know if this happens to you, people steal your food, and you get your soup spilled over everywhere. So they care more about service quality, and they do include that into this assignment score. Yes.

Audience:

So I thought that was interesting. I was wondering, you clearly only have data on one ride-share platform, but it seems like these assignment mechanisms could make it hard for drivers to kind of multi-home. And so they can serve as a little bit like an exclusive contract. And just again, you don't have two firms, so this is more of a simulation exercise. But do you have any idea of... If you can say anything about that

Yanyou Chen:

First, very good point. Not for this project, that's actually what motivates our project. We were first thinking about the locking, Nick mentioned. So this may drive drivers to be more loyal to a particular platform, but as I showed for our case, it is essentially a monopoly. So we don't have implications for how this work. For a follow-up project, we are looking at the competition between platforms and how this may affect the decisions for multi-homing and choice of single-homing. Yup.

Audience:

It's likely a monopoly.

Yanyou Chen:

True. Okay. Yep. Thank you very much.

Viola Chen:

All right. We need to along. Thank you for that. Our next presenter is Gregor Jarosch, and he will be presenting his paper, Dynamic Monopsony with Large Firms and Non-Competes.

Gregor Jarosch:

All right. Great. Thanks for putting this together and putting me on. I have no conflict of interest to disclose. I maybe should disclose that I'm a macroeconomist. So I might be talking and thinking about things a bit differently than most people in the room. But I think given where the literature is and also where regulators are on all things competition in the labor market, maybe, it's a great time to get people together that think about labor markets from different perspectives and get them in the same room.

So I'm looking forward to the conversation. So the papers joined with Axel who is at the University of Edinburgh, and I think on some level, it has two contributions that are a little bit disjoint and hopefully both interesting to the audience. The first is that we take the canonical job ladder model, which is the Burdett-Mortensen model and really modernize it, bring it up to speed for modern applications in the labor market.

So I'll tell you on the next slide how exactly we will generalize it. But I think of the resulting framework as a really natural laboratory to think about all things anti-competitive conduct in the labor market. Okay. And then we'll maybe take the prime application of that. And that's going to be the second contribution of the paper, which is to non-compete agreements.

And we have a set of theoretical results and that we have a model which I think is really modeling non-competes from the ground up and is quite illustrating in terms of how the economics of non-competes work. And we have some sort of stylized results that show that non-competes can, in particular, if they become widespread, really erode competition in labor market and probably suppress wages. And then we add, then, we'll put some numbers on it.

So to the first part, it's very much a modeling exercise. And so it's taking off the shelf, again, the canonical model of competition in the labor market for workers via posted wages, which is the Burdett-Mortensen model. There's been many, many features with the Burdett-Judd model, which many of you might be a bit more familiar with. And then we'll introduce a couple of new features that, as I think, are useful if you think of modern competition applications in the labor market.

The first is that we explicitly introduce size large employers into this framework. It's much a modeling exercise, but I don't think we've known how to do that, how to make that tractable. So that's sort of the first part. Obviously, then that allows you to meaningfully speak to things such as mergers in the labor market, market structure, and its impact on wages and so forth.

The second piece is that we'll be working with a decreasing returns to scale production function, which is also sort of a modification to the textbook model, which is linear. And obviously, as you know, we're decreasing returns that allows you to endogenize size and endogenize the response of market structures to shocks and policies and so forth.

The third piece is that we'll be having, it's still a bit dinky, but a model of the demand side with a market level downward sloping demand curve for the stuff that's being produced by workers, which is just a generalization of the standard model, which just has the price equal to one. And so what it allows you, and I think that's important, is to think how adjustment works in terms of quantities versus prices. So in terms of employment versus wages, we'll get back to that. I learned some sort of important lessons there.

And then the fourth piece, and that's maybe a bit more for the insiders of these models, is that we'll be changing the model in subtle ways that really sort of... Yeah. I'll try and explain that, on some level, change the economics quite a bit. So we're working with a hiring cost instead of a vacancy cost, which is the common modeling technique in models of frictional labor markets. That makes the model much more tractable. But I also think it gets to the much more important component of what's costly about churn and turnover, because hiring costs in many labor markets far exceed vacancy costs. So if you think of policies such as non-competes and banning non-competes that clearly affect what-

Gregor Jarosch:

... policies such as non-competes and banning non-competes that clearly affect worker turnover. You want to properly introduce and include the cost of turnover, and that's why we'll be working with a hiring cost.

Okay. So hopefully, I can convince you that the resulting framework is a natural lab to think about all things anti-competitive conduct. We're working on follow-up stuff that thinks about approaching agreements, that thinks about wage-fixing cartels in the labor market. Hopefully, I get a chance to briefly talk about that, but then again, the main application is on non-competes.

So just to briefly summarize what we do and what we find, so we have a set of theoretical results that basically just suggest that non-competes... Or show you how non-competes can just unravel competition for workers in a frictional labor market, and at least in the limit, would it become fairly widespread, really unravel competition. You get strong spillovers from the firms that have non-competes to the outside firms, to the outside employers, even those that might not have the capacity to write this type of contracts, to enforce these type of contracts and so forth.

We show one rationale why even based on purely utilitarian efficiency grounds, you might want to ban this stuff which induces misallocation of workers across firms. Then I'll talk a bit about welfare, and the welfare results are a bit ambiguous in the following sense. Worker turnover in these models is something that's actually quite inefficient because it generates a lot of churn. So competition generates churn, and that generates a lot of inefficient hiring cost, turnover cost. So an upside of non-competes is that they sort of economize on that. So, I'll get back to that.

Then we'll do something quantitative, a sort of interest a little bit in the comparative statics. Where would a ban really lift up wages? Where would it maybe not? So what we find is that there's some interplay between market concentration and non-competes. So banning non-competes lifts wages, in particular, in concentrated labor markets. It increases wages when turnover costs are high because that's when frictions are high, and so that's when anti-competitive conduct and rent extraction motives can really shift rent. Then we'll talk a bit about the role of the product demand.

As you can see, if the product market is highly elastic, then firms just can't pass through any of the rising cost from an increase in turnover to consumers and that basically has all the gains to workers evaporate. Then I have, just given that I come maybe from a bit of a different angle, a couple of things that might be sounding a bit pedagogical in the sense that some things we learned is that if you operate in this environment, you have to be a bit careful with some of the things we measure and we interpret if we live sort of in other settings. In particular, I'll talk a bunch about how to interpret quit elasticities, retention, elasticities, things people commonly measure now as a measure of labor market competition. Anyway, I'll get back to that.

Okay. So I don't want to talk much about the literature, but just to avoid any confusion, so I'm using dynamic monopsony in the title in the sense of Alan Manning who wrote a book 20 years ago, Monopsony Motion. What that environment does is it basically roots an upward-sloping labor supply curve to the firm in search frictions and worker turnover. That's quite different. An environment from the neoclassical static perspective, which basically has the labor supply curve at the firm level as a primitive. For people, again, it goes back to Robinson. There's prominent work now in that area. I want to be a bit careful going back and forth between these two settings. Again, sort of more on that later.

Okay. Let me jump in. I'll briefly run you through the key model ingredients. This first slide here is totally textbook, and then I'll say a bit more on where we innovate or deviate from the textbook. So it's going to be a random search environment. Workers will be searching when they're unemployed, and they'll also be searching on the jobs that is going to be something like a job ladder where they'll be moving along the job ladder through job-to-job transitions to turnover to higher-paying positions. The employed keeps searching with some reduced search efficiency as firms post wages and they commit to pay these wages.

They can, in principle, post a whole mix of wages, distribution of wages. I denote that by F of J. So workers are pretty mechanical here. They just become unemployed once a while, and they sample jobs, and they keep sampling while they're employed. So they drift up a job ladder. The only sort of meaningful decisions workers make in this setting is to choose a reservation wage. The important part is how firms basically pick wages or post wages.

Okay. So the hiring technology is a bit different. So firms can bring in workers as they want. So there's no search frictions. There's no vacancy posting or something like that. But whenever they bring in a new worker, they have to pay some hiring costs. So think of that as just onboarding costs, training costs, and whatnot. So firms do dislike turnover because they have to replace workers that leave to the competition, and that is costly. Okay? I don't know whether it will even need that, but denote by this object size of the rate at which workers make contact with an employer, i. Then we have a granular market structure.

So we have a discrete number of firms, and that's new. So there's no continuum of firms. Firms are not atomistic. They're large with respect to the market. Each of them will be employing a strictly positive fraction of workers in town. These firms have a decrease in returns of scale production function, sort of completely standard alpha denote in a span of control. Then I won't show you the math, but in the background, we basically reverse engineer with like quasi-linear utility, a downward sloping demand function for market-level output. You could modify that, but that's what we have.

We'll denote the elasticity by E. So I'm going to skip over the math in the interest of time, but let me sort of briefly just tell you how. Again, the firm problems are the key parts of how firms make decisions. So they will basically be choosing the intensity at which they advertise their jobs. That will relate into a sort of a contact rate or translate into a contact rate for workers, [inaudible 01:17:36]. Then they decide on offered pay. Okay? So denote that CEF by F of i. What do they maximize? Fairly standard. They maximize revenue net of cost. What are cost? Well, it's pay plus turnover cost.

So you can already see that that model still embeds the usual trade- off in these models between pay and turnover because if you offer more attractive pay, you sit on a higher rung-of-the-job ladder, so your workers churn less frequently to even higher-paying jobs, and then we'll model this as surface in a standard Nash equilibrium fashion. So I won't go through any of the math, and instead, talk a little bit about how we solve this, and then the lesson we learn, and then I'll turn to non-competes.

Okay. So the model remains super tractable. It's literally three equations and three unknowns. You can solve it paper and pencil despite all these new pieces, which I think, again, sort of make the model more flexible and sort of make it ready for maybe modern applications. So we have some algorithms in the paper of how to introduce a lot more heterogeneity on the firm side and still easily solve this. Here's a couple of results, lessons we've learned, and then we turn to non-competes. So in this model, you can think of what happens as market structure becomes more concentrated, say because of a merger.

What we find is that in the partial equilibrium sense, that does hurt workers because it just reduces competition in the labor market. Why is that? Because a big block doesn't compete with itself. So what matters here, what's competition is only outside competition. So to the extent that one firm consolidates more jobs under its own roof, that does reduce competition. So in a partial equilibrium sense, that reduces pay. But then what happens in addition is that churn falls and turnover falls. That, on some level, makes the labor market more efficient. These are basically productivity gains. In response to that, if firms enter aggressively and start hiring, then they might actually drive out wages.

So we call that GE, and it turns out you can't really sign that. So in principle, you can get that a merger here or more concentrated market structure can actually come with higher pay. Okay, a little bit on markdowns, so denote by M, the marginal revenue product of labor. Then you can show that for firms to be hiring optimally, the following must hold. So on the left-hand side, you have the markdown. So this is just literally the marginal revenue product net of the wage. So that's in the numerator. The denominator turns it into present values. So what's in the denominator? It's the discount rate, but then you also discount because the worker churns into unemployment and the worker churns to higher pay at the competition. That's the third piece.

If you hire optimally, then the present value of a worker, which again is the present value of profits that generates has to be equal to hiring cost. So you look at that, and that equation has to hold an equilibrium. So what happens if churn goes up? The denominator goes up because your worker state just transitioned to the competition more rapidly. The labor market is more competitive. So what has to happen? Well, the numerator has to go up too, so markdowns have to rise. So you get this tension between two measures that are commonly used to think about how competitive is the labor market, how well-off our workers, because here, it'll move in opposite directions. If churn is up, markdowns are [inaudible 01:21:27]. The final other thing I want to say on this is there's now a whole industry of paper set. There are people out there that measure quit elasticities, retention elasticities, these type of objects, and then draw conclusions on how well workers are off, how competitive the labor market is, and so forth. Where does this logic come from? It sort of comes from a notion that, in a highly competitive labor market, firms basically have to pay the marginal product, and you can't really deviate from that. So the quit elasticity or retention elasticity is really high.

Now, think of what happens in these type of models if competition completely unravels and collapses. In the limit, everyone is just paying the outside option. Everyone is paying workers the flow value of unemployment. So workers are in a really bad place. The labor market looks terrible. What's the quit elasticity? It's infinite because everyone pays the same wage. The outside option is the flow value for unemployment. So in this type of models, these measures can be really misleading measures for the type of things people make of them. So that's another sort of maybe some pedagogical comment.

In general, there is a clean neoclassical mapping between labor supply elasticity, these quit elasticity, and whatnot to things such as efficiency pay and so forth. But that mapping does not apply in these type of models of worker turnover that people commonly reference or work with. Anyway, let's turn to non-competes. So I think it's quite useful to sort of go back and ask how these models have evolved in understanding what non-competes do sort of economically. So you basically have in the '60s and '70s, McCall is what maybe everyone remembers from grad school. So repeated sampling from a dispersed distribution. When do you stop?

Then Diamond comes along in the '80s, and basically says, "That's all interesting, but it doesn't really make sense to assume these exogenous dispersed distributions because suppliers, what firms really should pose is just a reservation wedge." That's what people call the Diamond Paradox. So Burdett-Judd and Burdett-Mortensen are really responses to that. So you might be more familiar with Burdett-Judd, but Burdett-Mortensen basically says, "Look, if everyone pays sort of the Diamond equilibrium, what I can do as a firm is I can offer a little bit more attractive pay that comes with higher costs, but it gets rewarded by a drop in turnover cost because I'm doing a little bit better. I'm offering a little bit more attractive conditions than the competition."

These forces then unravel all the mass. So you basically have a resulting equilibrium wedge offer distribution that's really far from the Diamond world. That's sort of the essence of competition in these markets. So now, we'll bring in non-competes and basically argue that that can take us back to Diamond. So how do we model non-competes? It's very simple. As before, firms can. They post pay, but now there's additional clause that says you can't leave to the competition.

We do that in a very simple fashion, but you could do this in a richer way. So what do we find? We basically find that the firms that have access to this technology, they can enforce it. They start piling on mass at the... I'm sorry. I'm not used to talk for so long uninterruptedly.

Audience:

We can help you there.

Gregor Jarosch:

Go. Go right ahead. Okay, so these firms, they develop these technologies. They can write these contracts now. What they're doing is they pile on these jobs at the bottom of the job ladder. So from the perspective of the worker, these jobs look terrible. They offer exactly the same value as the worst job in town, the job with the lowest pay in town. Now, these jobs don't look so bad if you look at wages. In fact, wages look pretty good. Now, why do wages look pretty good? Because they contain a compensating differential for the fact that you basically sign your life away and you commit not to move and transition to better opportunities. Okay?

As you can already see that just in terms of wage differentials, that the wage is not very informative about values or how attractive the job is or how much damage a non-compete does. Okay? So I can't really... This is going to be hard without me pointing to the right spot, but you have on the left the wage offer distribution, and the blue, it's the equilibrium wage offer distribution without non-competes. It's just a uniform distribution. Okay? So then I'm going to give the first firm in the labor market access to non-competes. That's the red line. So what you can see here is that that firm posts a mass of jobs with pretty attractive pay. That pay is kind of in the middle of the distribution. Okay?

So now, you might say, "Well, that looks pretty good." But then on the right, you have values. So not just wages but the full forward-looking part, which includes the option value to climb towards more attractive pay. So there you can see or almost see that these jobs piling on, there's mass now at the very bottom. Okay? That's that piece of mass on the red line on the right. These jobs that look pretty decent in wage space look pretty terrible in terms of value space because they're, again, the least attractive jobs in town. Then you can basically show that from that, you get pretty strong spillovers to the rest of the market because these guys are basically no longer competing. They're sitting at the bottom of the ladder.

As a consequence, there's sort of less competition on the interior and all the other firms start reducing pay, and then reservation wages start falling, and so forth. So you get this general equilibrium effect and things start deteriorating for workers. What's the limit? The limit, you can sort of see it. I don't have to pay you a compensating differential anymore. Everyone signs a non-compete. Everyone gets exactly B. Nobody has any incentive to deviate and offer something more attractive because there's nobody to be poached because everybody's under non-compete. So think completely unravel and you restore the Diamond equilibrium that you've sort of undone with the job ladder competition forces prior.

Okay. So I guess that's what this slide is saying. I mean it's obviously stylized, but it's just to point out that once these technologies become or contracts become widespread, really has the potential to unravel competition in these type of markets. We have a bit more on welfare. So there's a couple of things there. The first is that what you can see is that, these firms in the basic model, all have the same decreasing returns to scale technology. So you don't want them to have different size because that means misallocation because that means there must be a differential margin product of labor. So when do you get that? You get that here, because these guys with the non-compete, they have a lower user cost of labor, so they'll be larger in equilibrium, and so that's something. That's an actual welfare cost of non-competes to the extent that only some firms have access to it.

At the same time, the nature of competition here is relatively wasteful because it's basically job hopping that generates a lot of turnover costs and so forth, and that competes rents over to workers. So from a purely utilitarian perspective, reducing that churn via non-competes, actually, can come with some gains. Okay? So numerically, when we take this to the data, put some numbers on it, we usually find that banning non-competes, actually, in utilitarian welfare actually drops. A bit more on this in a second. Now, one caveat here is that this job ladder that I'm modeling here is not allocative. It's not that it's sort of taking the workers to where they need to be, the right person to the right job. So that will be obviously something to consider in a richer setting.

Okay. So I'll spend the last couple of minutes on telling you a bit about the numbers we put on this. So much of this is pretty easy to quantify, at least for how I work with these type of models. We basically do a bunch of robustness for the things we don't really know how to calibrate. The one thing I should say is that we're setting the hiring cost to monthly wages. So that we're doing it with one and five, and then we set the remaining parameters in an application-specific way. Now, I don't want to go into detail here, but basically, what we're doing is we're doing two-model validation calibration-type exercises with the Prager and Schmitt paper on hospitals and with Lipsitz and Starr on... I think, it's actually '22 with a ban of non-competes in Oregon. Anyway, let me skip over that.

I don't have to tell anyone in this room what's on this slide. So it's just we're trying to at least back off the envelope, get the numbers right. We'll be working with 10 symmetric firms, 2 of which have access to non-competes, and then ban it. We calculate the equilibrium and ask what happens to pay, to price, to turnover, and so forth. So this is our baseline result. So again, before we ban it, a bit over 20% of workers are on non-competes. When we ban it, we get about a 4% increase in pay. That comes with an increase in unemployment, so reduction of employment. Why is that? It's because pay is up, but it's also because turnover is up a lot, and the increase in turnover makes firms pull back on the labor demand.

So the other thing you get is that utility is down. Again, it's coming from the fact that churn is up, but it's also coming from the fact that the higher pay gets passed, at least partially, into higher prices, and then to the extent that these workers also consume this stuff. On some level, they pay for the higher pay. So it matters also who's the consumer. Okay. We do a bunch of comparative static, ask how do these things change when the training costs go up, when the market is more concentrated, and so forth. One thing I've learned is that the demand of elasticity is really important. In particular, if the product market is highly elastic and the employers can't pass the rising cost into prices, then basically, they pull back on employment up until the point where all these gains from banning non-competes to workers actually evaporate.

So we found this really important role for the product market. That's something I didn't see coming up front. You can get large effects to the extent that the market is concentrated, and say, half the market uses non-competes and you ban it, wages might rise up to 20%. So you can get a very strong effect. It really depends on local market characteristics. Okay. We do a bunch more things, but hopefully, you get the idea. So I have 30 seconds, so maybe I'm just going to advertise what we're working on right now. So the framework, I think, is quite natural to think about other forms of anti-competitive conducts, and we're now thinking about what people call the wage-fixing cartels, where a subset of employers in this type of environment sort of agree on a wage ceiling or a going rate or something like that, and then we basically work it out in a model. Anyway, I am out of time, so I'll leave it at that. Thanks a lot.

Speaker 3:

To discuss the paper, we have Heski Bar-Isaac.

Heski Bar-Isaac:

Awesome, thanks. So thanks for including me on the program and for having me here. Disclosures, I'm currently visiting the Canadian Competition Bureau, though the usual disclosures, everything I say is in my own views. There is relevance in that I'm at the Competition Bureau because many of you may not know that the Canadian Competition Act has changed dramatically over the last few years. One of the things that it now explicitly incorporates is labor market considerations. So if you're interested in that, speak to my Canadian colleagues over here.

That said, I haven't done any specific work on labor. In terms of expert work, I've done exactly one thing as an academic about five, six years ago. But funnily enough, it was for a labor union, so it's for the communication workers of America, but on nothing related to this. It was all of, I think, eight hours paid work. So I don't think it's a massive issue. I should also disclose that I don't do macro. I think I was asked to do this because I do labor theory, but usually, in a sort of partial equilibrium way. I don't know how many people here have read David Lodge, but there's this famous scene called Humiliation.

I hadn't read Burdett and Mortensen before coming to this paper, even as a labor theory guy. I don't know how familiar it is to everyone in this room, Nobel Prize winner notwithstanding. So let me just kind of step back because I think the philosophy of where this is coming from is very different from what many people in this room are used to. So there's no size or other Greek letters that we don't know how to pronounce. This is from a very different tradition that, to some extent, starts with Stigler as Gregor highlighted, where we're thinking about this puzzle that says, "For things that look completely identical, we see dramatically different prices." I think that that's a lot of the spirit of this Burdett and Mortensen paper.

This is jobs. They're all the same people are all doing the same things, and yet they're paid vastly different amounts for it. So how should I think about that? The way they think about it is actually quite aligned to how the IO literature was in the '80s, '90s as well, which said, "Well, there's going to be some mixed strategies." Right? Those mixed strategies, they're coming about in the kind of ways that the IO people might be familiar with from things like Edgeworth cycles or something like this. We're going to kind of undercut, but there's some loyalty. I'm trading off this loyalty against this better price, and that pans out in a kind of mixed strategy sort of way.

What's really cool about the Burdett-Mortensen framework is that happens in some dynamic contexts, how long people stay in the job, and that's spirit of it, and that's the framework that Gregor is really going to build off for good or bad. So I think it's important to kind of understand in that context. Now, I've already used up about half my time and I haven't gotten into any of the slides yet, so that's not great. I anticipated that the presentation would be absolutely crystal clear because the paper is extremely polished, extremely readable. If you're interested, then reading it will add a lot more value than me waving my hands around.

I think, normally, these discussions start with a few minutes of motivation. Why do you care about non-competes? Why would anyone in this room be interested in labor markets? I'm going to skip over that, and I think I'm going to skip over the overview as well. I mean, I think Gregor set out that builds off Burdett and Mortensen, but incorporates features that makes this more amenable to the kind of analysis that people in this room will be interested in. So we want to take large firms seriously, so we better incorporate some non-atomistic firms. We want to think about the size of those firms, some product market effects, and so on.

What comes out of it is very sensible. Fewer employers means wages are dampened and so forth. Okay. So in more detail, this was mostly to prove to Alan that I'd done some homework, but let me skip over that. Let me get to the stuff that is more... I mean, it's already been pretty idiosyncratic. I'm explicitly not going to say anything about calibration and validation. It's not my value-added. The two papers that were calibrated against, some of the authors are in this room. So I see Evan. I saw Eli earlier. I'm not going to embarrass myself by trying to cling to, you know. I'll move on.

So I'll do the things that discussants are supposed to do, which is moan a little bit about the paper. That moaning is not because I think that the paper is not a fantastic paper. That's just to say these are aspects that we can push and think about. So my starting point is always to ignore the paper and think about the issue. So when I read newspapers, when I talk to colleagues about non-competes, what are they thinking about? They're thinking about, "These are bad for workers because they're going to dampen wages, and these are bad for workers, going to stop workers moving to the right places." But why do these exist? Why might they be a good thing? Well, they might be a good thing because this cost of people moving about.

I think in the popular literature, we worry less about churn and worry more... There's issues around firm incentives to invest in IP, kind of trade secrets aspects and firm investments to invest in training that might then be expropriated by other firms. I think the other thing that I know about, from the world, is that there's heterogeneity in the prevalence of non-competes. That's an aspect I want to kind of come back to as well. So what does this paper captures? Wage effects? It's very well set up to capture that these non-competes are dampening down wages. In terms of misallocation, yes and no, I would say. I mean the baseline model, everything is homogeneous. All these, we call it a job ladder. Really, we mean a wage ladder. They're all doing the same thing in the same kind of firms.

We can throw some heterogeneity on the firms in terms of productivity, and that allows for some notions of misallocation. But I'd rather be at a job that's a five-minute walk from my house than an hour away from my house. We don't capture any of that or any of the things that normally live inside the size and other Greek letters you guys like to use so much. So I mean, I'm being glib, but I don't quite know how to think about that, how seriously to take that misallocation. What about the good of the non-competes? Gregor, in the paper says, "Well, a lot of this is happening at low-wage jobs, the kind of famously Wendy's non-competes or whatever fast food chains." Hard to think that they're really trade secrets there.

Is it so hard to think that there's investment in human capital there? That, I'm less sure about. I mean, famous McDonald's University, whatever it is that they do. But also, you can think about setting up the firms and organizations in such ways that you're substituting some capital for specific human capital. There do seem to be real choices and decisions to be made there, and that's captured a little bit by the kind of hiring cost here, but that's treated exogenously. It's not responding at all to any changes in non-competes or anything like that. So it's worth a little bit of thought as well.

How about observed heterogeneity in the prevalence of non-competes? We said there's 20% of them out there. Here, I think it's true that the paper calibrates, sets that, but completely exogenously. So for an outsider who's trying to say, "This is a paper that, to the extent, wants to be about non-competes and just assumes that some firms randomly have them and others don't." That's a little bit unsatisfying. It'd be nice to understand what the source of that heterogeneity is because that might give us some clues about what it's doing.

Heski Bar-Isaac:

Some clues about what it's doing. Okay. Bottom line though, this is a very nice, very cool paper. It's calibrated macro, so it's not going to do everything that you want it to do. We have to make compromises in our work no matter what. And if you're trying to capture the whole economy, then the compromises are going to be rather grander as well. There's this empirical validation is reassuring, the effects and the scale of the effects seem plausible, and it's a very tractable model. Like you said, you can solve it by hand, and so that seems like there's scope for lots of bells and whistles to get at this. I'm not very well-known for my research or anything else, but to the extent I'm trying to build my brand, it's around poetry. So you can go on my website and you can find lots of haikus, some on my work, some on others. The haiku for this one gets at the general equilibrium effects as well. So banning non-competes raises wages 4%, but also prices.

Speaker 4:

We have a few minutes for questions.

Speaker 5:

Great paper, and I learned a lot, partly also but [inaudible 01:46:33]. But I'm interested in the last part of the haiku summary here. How much do prices do actually go up under the 4% scenario of wage increase?

Gregor Jarosch:

Yeah, I should first say thanks a lot for discussion. That was really great. So I don't know off the top of my head, but in the baseline, much of the pay raise gets passed through, so it's not much less than 4%. That's right.

Speaker 6:

You talked a bit about... [inaudible 01:47:11]. You talked a bit about how the standard elasticities we estimate aren't that reflective of some efficiencies we're trying to measure and wage markdowns. Are there any obvious corrections or complementary measures we can estimate that will provide a better picture?

Gregor Jarosch:

I wish I could do that. We tried hard working in that direction, but I unfortunately can't. The one thing I can say is that we've done a lot of experiments in the model, have entertained different shocks and policies. And that usually the market level average quit elasticities and worker well-being wages were exactly going in the opposite direction than under the neoclassical setting. So I don't know whether there's an easy fix to it.

Speaker 7:

So first of all, thanks for a really pretty presentation, I actually learned a lot from it. You explained I think the general framework so well, it makes me want to go back to the first couple bullet points, which is, if you're at the FTC and you're a regulatory agency, when should you take this more macro approach, and when should you maybe think this is more like a classical monopsony that's more like Cournot, or differentiated jobs, Bertrand or something like that. I think to some degree, you might be calibrating to some bit of one and a bit of the other. And it might be important to think like, what's the context for one and what's the best context for the other.

Gregor Jarosch:

Yeah, I'm very sympathetic. I think that maybe we're at a stage in terms of at least of the academic literature where we should just be having a serious conversation about what is a good model of employment and wages? Is the static monopsony model that now lots of people are using, and that we sort of imported from really the consumer side, and just in many ways just flipped upside down, and we sort of skipped the step almost assessing whether that is indeed a good model of employment and wages. And I think maybe we have to take a step back and argue that, and then maybe we can learn the answer, which I don't think I have a general guidance in terms of when to use which model. But I think it's a conversation we need to have.

Speaker 8:

One of the arguments made in favor of-

Speaker 4:

Oh, sorry, can you wait for the microphone?

Speaker 8:

Yeah. One of the arguments made in favor of non-competes, at least in very specific situations, specific roles and so on is that, in the long term, if non-competes weren't allowed, it would disincentivize investment in training and exchange of technical skills, and could lead to a lot of companies protecting that through trade secrets, which would prevent knowledge transfers in the long term. In the long run, that could have theoretically some negative effects on job opportunities, also possibly on wages. So is that something that you guys have considered?

Gregor Jarosch:

Yeah, so I think it's a little bit there. I think it was in the discussion also in the sense that you can think of, firstly, the employer that brings in a worker has to train them. That's part of that cost. And to the extent that the worker churns more rapidly, they're less willing to do that. So you can on some level, think of them pulling back on hiring as they're now less willing to invest into new workers, because they will leave more rapidly. What we don't really have in there is some notion of on-the-job training.

Speaker 4:

All right, thank you so much. And now we're going to take a break and we will reconvene at 11:15. Hello everyone, we're going to get started again. If you could please take your seats. All right, if everyone could please take their seats, we're getting started. Next on our agenda, we have our first keynote address. Our first keynote address is given by Allan Collard-Wexler. Allan Collard-Wexler is a professor of economics at Duke University, specializing in industrial organization and productivity analysis. He's also a research fellow at the National Bureau of Economic Research. Give you, Allan. Just the green button [inaudible 01:52:34] forward.

Allan Collard-Wexler:

Oh, thanks. I see. All right. So this paper is going to keep on the topic of market power and labor markets. So it's going to be a paper on Oligopsony and Collective Bargaining. And just to announce, it's a paper that's joint with Tirza Angerhofer who's in the audience, who's a grad student at Duke, and Matt Weinberg who some of you probably know from the year he spent at the FTC. All right, so the research question of this paper is trying to understand the consequences of oligopsony power, that's like monopsony power but with many different employers. And collective bargaining in the market for teachers in Pennsylvania. And so what I think is interesting about this is that just to focus on teachers for a sec, is this is a profession that has very specialized skills. You have to do an education degree. Those skills aren't really fully transferable to other occupations.

But if you think about who the employer of teachers is, they're kind of local school boards, so they're like local monopolies of the teaching market. And so like a of occupations that are mainly governmental, there aren't a lot of employers in that sector. And so this leads to a problem of oligopsony power. Now what got me thinking about this is a lot of discussion about monopsony power is fauxed about things about minimum wage, or thinking, "Well, maybe we need to prevent concentration of employers to begin with." And those are kind of interesting mechanisms to deal with monopsony power. But the classic mechanism that people have used in practice as collective bargaining and things like unions. And so there's an old Galbraith line about, "If you have very concentrated employers, maybe you want to have very concentrated employees as well." Or in other words, maybe the thing you want to do to counter market power in one side of the market is have market power in the other side of the market. So market power is the solution to the problem of market power. And we see this a lot in the rest of IO, cases like, I'm trying to understand bargaining between cable TV operators and content providers. So think of the work by Ali Akoglu. Cases trying to understand bargaining between health insurance providers and hospitals has really tried to think about the tools that you need to analyze concentrated markets in both on the upstream and downstream. And the goal of this project is to think, can those tools be used to analyze the employment market for teachers?

And I'd also add, unions are prevalent in a lot of places in the world, so like 40% of Quebec's labor force is unionized, or all of Germany uses sectoral bargaining. And there're not many unions in the United States, but where you do find unions are actually in the public sector. So this is the place where we see them the most. So with that in hand, what does this paper do? We have got very detailed granular data on teachers in schools in Pennsylvania. If you're following the last discussion, and Heski was asking about the things that IO people do with Greek letters. This is like a representative of that approach. We're going to use this Nash-in-Nash bargaining model that's been used extensively in IO to understand markets where there's power on both sides and apply it to the setting of collective bargaining for unions.

And I should just stress, a lot of that work was set up to understand different type of mergers that were going to be analyzed, that people in this room have worked on. We're going to apply that to the labor market. So a lot of the goal of this paper is to try to port over some of that work to the labor problem. And we're going to use this model to think about what's the efficiency of unions, what are the outcomes if you don't have unions, what are the socially efficient outcomes? So try to do kind of a welfare analysis in this context.

All right, so let me just give you some setting. So do the IO thing of diving into the details. So we're going to look in Pennsylvania, there's about 500 regular school districts. There's also a number of charter schools, but most people work in a regular school district. And the way that regular school districts set wages is through a collective bargaining process with teachers' unions. And more importantly, each school district has a local teacher union. So the bargaining is going to happen at the school district level on both ends. The second thing is, to the extent that monopsony power is distortionary, it's really important that when you hire an additional worker and you have to raise the wage to hire that worker, you also have to pay everybody else more. And to make that very clean, you need something like uniform wage schedules.

If every worker gets paid a different amount of money, it's a little bit harder to understand how that distortion is going to work. And here, the setting is going to be simple. The amount you get paid as a teacher depends on, do you have a master's degree, and do you have up to 12 years of experience in teaching, more or less? So a very simple kind of salary schedule context. And the other thing to say about Pennsylvania, say for instance North Carolina, where wages are pretty much even across school districts, is there's a lot of variation. So Lower Merion outside Philadelphia has average wages of about 100,000 in 2016, versus other school districts like North Star have wages under 50,000. And even school districts that are close to each other like Philly versus Lower Merion that kind of border each other, have differences in wages of 70,000 to 100,000. So these workers are getting paid different amounts even in very close-by labor markets.

All right, so this is just a map. All the school districts in Pennsylvania. There's a lot of variation, like Pittsburgh has... Allegheny County has 63 school districts and then there's other parts of the state that have fewer school districts. So just going through the classic, I guess Gregor called it neoclassical. So this would be what we'd think of just this static model of the monopsony distortion. There's a labor supply curve in red, there's a labor demand curve in blue. And because to hire an additional worker you have to pay a higher wage, and then you have to pay a higher wage to everybody else that got hired. The marginal cost of hiring a worker is above simply the wages that you pay. So the labor, the factor cost curve is going to be above simply the labor supply curve.

And so the efficient point would be at a point like A. Oh, sorry, I'll go back. I guess this wouldn't work. The efficient point would be at a point like A, but the monopsinist is going to basically choose a lower wage, which is going to be at the intersection of this blue line, the marginal benefit of labor and this kind of dotted marginal factor cost. So the monopsinist is going to choose fewer workers and a lower wage. Now let's try to think of what happens if there's say a collective bargaining agreement. In this context, it can choose a different wage. So it doesn't have to choose the monopsinist wage. It can choose a wage that's higher or lower than the market clearing wage. So here I've just drawn it where they choose a wage that's above the market clearing wage. Here, there's going to be a different issue, which is, is the number of worker hired going to be on the labor supply curve, or is it going to be on the labor demand curve, right?

Because there's a difference between labor supply and demand. I'm going to use something that in the literature they call the Medoff union model, which is, we set wages, but then employers get to hire the number of workers that they want to hire. So in this context, they're going to hire the number of workers at the intersection of that green line and the labor demand curve. So they're going to hire fewer workers than at A. So the idea being if wages are above the market cleared wages, employers will hire fewer workers, and that also causes a deadweight loss. So what you can have are deadweight losses that come from monopsony power. And then you could have a collective bargaining agreement. And depending on where that agreement ends up, you could have better outcomes than monopsony, worse outcomes than monopsony. So there's really an open question of is this kind of collective bargaining improving or making things worse?

And so I think that's the goal of this paper is just quantifying what those deadweight losses of monopsony and collective bargaining look like, and how much do they offset each other. All right. So the model is going to have three stages. At the top stage is going to be a wage formation process, and it's going to be a Nash-in-Nash bargaining process. So first of all, it has to be a bargaining process because wages get negotiated. The second Nash in there just refers to the fact that the wages that I negotiate with one school district, because all the workers are in the same labor market, are going to affect the number of workers that want to work for other school districts. And so that creates kind of externalities across the negotiations. And so that's why we need this kind of tool.

Given the wage, school districts are making hiring choices. So there's going to be a hiring model. And the really tricky thing about this hiring model is if the wage is above the market clearing wage, then you don't want to give a job offer to everybody. You want to hire fewer people than the number of people who show up. So there's going to have to be some kind of rationing rule to figure out who you're going to hire and who you won't. Finally, teachers have offers, and then they decide who to work for. And again, what's tricky is that since employers aren't giving jobs to everybody if the wages are too high, teachers can't choose between all employers. They choose between the employers from whom they get offers from. So there's kind of a subset of the employment opportunities that are available to them.

And so this is going to cause a number of different challenges at all these levels, and we're just going to basically drive through to show you how this model would work. But I think the kind of key idea here is that when wages are set by something other than market clearing wages, you could get excess supply of labor, and that changes outcomes is kind of critical to this model. All right. So let me do a little bit of preliminary evidence. Just, teachers aren't everybody, but they're 1% of the workforce. So they're a big labor category, and they need specific training. And the government's the dominant employer, and they get paid based on uniform wage schedules, which makes the modeling straightforward in this set.

Not only do we know what a teacher makes in their current job, but we also know because of these schedules what they'd make anywhere else. So it really helps us kind of fill in what the alternative wages would look like in a way that's unusual. So this is a map of all the school districts in Pennsylvania and the kind of darker blue is kind of higher wages versus lower wages. And that you can see a lot of wage variation here between 100,000 and say 37,000, with these kind of darkest areas being in the kind of Pittsburgh and Philly metro area. There's also variation in concentration. So in particular, there are places like Central Pennsylvania where if you take all the teachers and ask of those teachers what fraction of them are hired by the same employer? The answer is like 95% of them.

So there's some places where really everybody's hired by the same employer, versus if you look around Pittsburgh. If you take the teachers and ask teachers in a 10-mile radius how much are employed by the same employer, the answer is less than 5%. Again, Allegheny has 63 school districts, so there's kind of variation concentration. So I just showed you a wage thing and then I showed you a concentration thing, and then let's plot them against each other. So I call this the Forbidden Regression, the kind of price concentration regressions. I think in this context, the issue of the endogeneity of the market structure being related to the wages are a bit less just because the school districts get formed quite a while ago, and aren't formed just in response to the wages.

But would all the caveats that everybody in this room knows about doing kind of price concentration regressions. The left panel just shows you at a region level, like Philly, Pittsburgh, you know, what's the relationship between local Herfindahls and wages? And then you can also do it more locally. Like if you just look within a school district, how does the presence of neighboring school districts seem to be correlated with wages? You see more school districts seems to mean higher wages. So this is just some preliminary, yet tricky to interpret evidence.

The other piece of evidence that I like to think about is one of the things that happens is like, think about a school district and they're deciding how many people to hire. Then there's a question, they have a fixed budget, so what do they do if they don't hire a teacher? They spend it on other things like soccer fields, or tablets, or psychological services for students, and I'll call that X. And in a market where there's no monopsony power, the kind of iso-budget lines... Or just the iso-budget is just a line. But in a market where the more teachers you hire, the more you have to pay them, instead of having a line to represent this kind of isocost, you actually have a curve. The more teachers I try to hire, the more expensive they are.

So I get a curvature. And so if I'm plotting out the Engel curve, how many teachers do I hire as I scope out the budget? As my budget goes up, I kind of tilt my expenditures towards the non-monopsonized input. So I start tilting expenditures away from teachers and towards soccer fields, or computers, or that kind of stuff. So this kind of gives an implication that the Engel curves are going to look different in markets that look very monopsonistic versus markets that don't. And so this are just kind of evidence that shows that on the left, you have competitive markets, on the right, you have concentrated markets. In markets that are more concentrated as budgets go up, you get more spending on non- teacher inputs. And so that would be consistent with this kind of distortion from monopsony power. All right.

And then the final piece of evidence is, there's a part of this sector that's not unionized, and those are charter schools. And the wage difference between charter schools and regular school districts is enormous. So like 68,000 versus 50,000, again for comparable markets. So there's a lot of things that are different between charter schools and regular schools, but the kind of mere fact that the kind of collective bargaining agreements don't work for charter schools looks like it's leading to very different wage schedules. And that could also be evidence of bargaining being important. Often when you see wage differences, your first answer is, "Well, maybe one's a hard job and one's an easy job. And those are just compensating differentials." But in the data, it looks like the charter school teachers quit a lot more. So it's hard to square away the fact that charter school teachers quit a lot at a given wage with charter school jobs having a compensating differential somewhere else.

All right, so this is kind of the preliminary evidence. And then the final one for bargaining and wage dispersion. So I guess we all have a device in these models for people getting different wages. The device in this model is going to be bargaining. So if you compare teachers, say in different suburban Philly school districts that are next to each other, the wages differ a lot. And it's hard to think of commuting time or preferences explaining those differences, especially since the school districts that pay the most aren't the school districts that are thought to be the hardest to work with.

So high paying school districts tend to have also fewer kids on free lunch and other characteristics that teachers seem to like. And so we think that the kind of difference in wages between school districts, given that those difference in wages are correlated with other things teachers like, is indicative of bargaining frictions that kind of lead to different wage outcomes. So that's the other piece. And then as a final piece, you might worry that they're hiring different types of teachers at different school districts, but if you kind of follow these teachers when they leave a school, it's not that they are at a high paying school district, move across the state to another high-paying school district. They kind of move from a high-paying school district, and then when they move across the state, they go to basically an average school district. So there isn't the same kind of sorting in terms of how people move between jobs, that would be indicative of an unobserved quality attribute that's generating that.

All right, so let's get into the structural model. So three parts, three pieces. And I'm going to do them in reverse order. There's a supply curve. Teachers are going to make decisions about where to work. There's a labor demand curve. School districts are going to make decisions of how many people to hire. And then at the top, there's kind of a wage formation process. I'm going to call it Nash. It's going to be this Nash-in-Nash bargaining. And I'll do the caveat. It turns out that the limit of the Nash bargaining process as the school district gets all the bargaining weight is the monopsony wage posting model. So this Nash bargaining model is going to nest wage posting as well. Okay, so just to give you an idea of what the data looks like, here's a picture.

If you're not familiar with Pennsylvania, this is what Erie, Pennsylvania looks like. So Lake Erie is at the north, the black dots are the location of all the teachers. So from the State of Pennsylvania, we get the names and salaries of all the teachers. And so we then match them through InfoUSA to their home addresses. So this is where all these teachers live. The blue dots are regular school districts. The two red dots are charter schools. So you should think of the school districts are making offers to... the blue dots are making offers to the teachers in those black dots, and then they're deciding where to work. And we've computed the time it takes to commute from your house to any of these school districts in kind of the local area.

So we have this commute time that's going to lead to horizontal differentiation between schools, that's going to be part of the monopsony power. All right, so that's our data. So let me start off with labor supply. So I think this is definitely ripped off from the consumer side part. People have a utility of working in any school district. They care about things like wages. They care about the time it takes to commute, and that leads to this horizontal differentiation. They may also care about other school attributes like, is this a charter school, or just a school that has a lot of kids on free lunch? So those are going to be the Xs.

And then they have this epsilon logit shock. So the lack of substitution between schools, condition on a wage is coming both from commuting and from the logit shock. So that's what's giving us our upward sloping labor supply curve. Now what's really tricky is that if you don't get an offer from every school, which is going to be true in our model, then you choose the best option among the offers that you got. So again, if you've been spending time in IO, this looks like an unobserved choice set problem. And in practice, you'll have people living in a very rich school district commuting 45 minutes to a school district that doesn't pay a lot.

And if you don't have this mechanism while they just didn't get an offer in that good school district, then you're going to say either people don't care about wages or they don't care about commuting distance or both. So you get very misleading demand estimates, and that's going to be important. All right. The second piece is we have a model of hiring. And here, the fact that this is government and not a private firm, means that we don't have profit maximizers, but that's fine. We have a school allocating budget between teachers and non-teacher inputs. It's going to choose to exhaust its budget because that will maximize this kind of W educational outcome function that it cares about. This is Cobb-Douglas. So you're just going to get kind of a simple expenditure. Shares are going to be pinned down to the coefficients of that Cobb-Douglas. So that's going to lead to basically a labor demand curve.

We realized, I think after comments, we should really be using something like a CES because this is going to give us kind of isoelastic labor demand curves, which is not great. So we're moving to kind of having a CES that lets us have different elasticities of the labor demand curve that aren't captured by this kind of production function. And then top, Nash bargaining. And here, let's just go over what the Nash bargaining piece is. You have the objective function of the school district W on one hand, you have the objective function of the union on the other hand. So the simple way we're modeling this is the school district either hires these teachers, or if the agreement breaks down, they get nobody. And then in their model, if they get nobody, they get payoffs of zero. So that's why we're just thinking the relative payoff of the school district is just this W thing.

On the other side, we needed to endow the union with an objective function, and people have talked about that, but I haven't seen any actual structural estimation of a union model. So here we're going to assume the union cares about total membership dues, so there'd be total salaries paid out to union members. The critical thing here is that we need the union to care more about wages, and the school district to care more about hiring the number of teachers, otherwise kind of results get flipped. Then the final thing is we're going to have these bargaining parameters differ by school district. So if you've say looked at Matt Grennan's work for instance, on bargaining, it's going to be the same kind of thing. So we're going to allow for that bargaining parameter lead to different wages even with the same observables on everything else. Okay. All right.

What's the second Nash part here? Well, the number of people I hire depends on the wages that other people are setting, so that's why we need to kind of be putting in those externalities. All right, so let's get into estimation of this. So we've got a big model with lots of Greek letters, some beta, some tau. Okay. They're both Greek letters that refer to the labor supply parameters, like how teachers choose between schools. And there're also Greek letters that refer to labor demand parameters, how school districts substitute between hiring teachers and spending money on other things. And then finally we have Greek letters associated with the bargaining weights in the Nash bargaining, which tell us how much of the surplus gets soaked up by the school district, and how much of the surplus gets soaked up by the labor union. So we have all these three pieces, so we're going to proceed backwards.

I told you that people don't get offers from every school district. And the question is, what are you going to do? We were reading one of these McFadden papers to try to understand that. And one of the implications of the logit IIA is that if I want to know the relative probability of choosing job J versus job K, it really only depends on the difference in utility between those two jobs. And importantly, it doesn't depend on what the other jobs would look like, do you have access to them or not? So using a logit and this IIA means that we can look at the two things that we know are in the choice set and the relative choice probabilities to identify the model. So then it's like, "Well, what are the two things that you want in your choice set?"

And I think what we settled on was nobody really ever gets fired as a teacher. So staying in your job is always an option. And then quitting is always an option. So taking the outside option. So essentially, we're using for all intents and purposes, like a quitting regression to identify the labor supply parameters. Okay. All right, so that's what we'll be doing. So these are some estimates, let me actually just... These are hard to interpret, so let me kind of convert them into kind of marginal rates of substitution. So we have commute time, salary characteristics of the school. So what we get is that the marginal rate of substitution between one more hour of commuting, and that's like teachers work 200 days a year, they have to go to school and come back. So we're kind of scaling. One extra hour of commuting on a day is worth about $76 in terms of how it gets traded off with wages of different schools.

And then schools with poor kids or charter schools are heavily disliked. And then the own wage elasticities we're getting are between four and five. So we're getting fairly elastic own wage elasticities. We also did a bunch of work with a nesting parameter just to make sure that there's correlation between the decision of working in two school districts versus the decision of quitting.

Allan Collard-Wexler:

Between the decision of working in two school districts versus the decision of quitting. And that's going to be really important. When I decide to leave this school district. Am I moving to being a secretary at a dental hygienist am out of the schooling sector or am I moving to nearby schools? That different in substitution is going to be critical. All right. So here are unreadable tables of elasticity estimates. What I want to say is if everybody got a job, you get elasticity estimates of about five and we get different kind of substitution patterns to different schools. So one to 15 or just other schools, O is the outside option.

What I want to emphasize is if you actually look at what the elasticities are, when people only get to choose between the offers that they get, those elasticities are way lower. So on the order of one to .8. Again, I'd like to emphasize because we have a bargaining model, you don't need to have elastic labor supply. You can have an elastic labor supply and that's fine, but the observe kind of lack of switching can be kind of attributed in large part to the fact that people aren't getting offers from everywhere. So the low amount of switching is misleading about teachers' underlying preferences and that seems to matter.

Okay. For estimating labor demand it's like estimating a labor production function. So if you've ever estimated a Cobb-Douglas production function using labor shares, that's what it looks like. So that's what we're doing. I think the thing that was important to us is it turns out that for every dollar and wage that teachers, they get about 50 cents of other benefits like retirement and medical. So it turns out non-wage compensation was a huge part of compensation in the sector and that was key to open up. Okay. And then there's one more twist here, which is it turns out that you might observe T workers hired because that's what the school district wanted or you might observe T workers hired because they basically ran out of workers to hire.

So there's a little bit of a censoring problem that we have to attribute as well. So these are pictures of labor demand and supply curves that we're getting out of our model. Okay. And then the final piece at the top is this kind of Nash bargaining parameter estimation. So we have an Nash product and we're kind of taking a first order condition to kind of estimate Nash bargaining parameters school district by school district. We did something which is since the charter schools don't have unions we pin down their bargaining parameters to one, the school district gets to take it or leave it offers. And so these are going to be estimates of these bargaining parameters.

And so the ones that are at the top towards one that's just the charter schools and then you see all this variation in these bargaining parameters. At first I thought that people pay different wages because the school districts have very different budgets per student, so there's enormous variation in Pennsylvania and how much gets spent per student, but it turns out the bargaining parameters and budgets aren't that correlated. So we felt a little bit more comfortable thinking of them as exogenous things in the background. All right. Okay. And let me move on to the relevant counterfactuals we're thinking about. So the first one is, what does the world with posted wages look like?

What does the world with the social planner or as people at Chicago told me the intersection of labor supply and labor demand, what does those look like? And then what do wages look like under the Nash bargaining model that we've estimated? Okay. And so I'm going to be presenting kind of simulations for the entire state of Pennsylvania. I'll be showing you weighted median wages just indicating that outliers are still an issue in this model. The average wage that we see in the data median wage is 55,000, and there's 107,000 teachers that are employed in Pennsylvania I believe in 2016. If you look at the Nash bargaining predictions, they would predict 56,000 and 107,000 teachers.

So the real and the Nash bargaining predictions seem fairly in line with each other, at least at the aggregate level. And this is not merely mechanical because it turns out that it's possible that given the bargaining parameter, those school districts would choose a different number of teachers than what's chosen the data so this is not completely just because of in sample fit. If you think about what the posted wage would be, that looks just like you drive up the bargaining parameter one for everybody, the school district next has all the weight, then now you have wages that would drop from 56,000 to 45,000. So this seems to be quantitatively a large wage increase coming from this bargaining parameter on the part of school unions.

One of the nice things when that happens is that when the wages go down, it turns out the school districts are going to hire more. So instead of 107,000 teachers you have 119,000 teachers. So there's a positive offsetting effect there. Turning to the planner solution, this would have wages that are $5,000 higher than the posted, $ 6,000 less than Nash bargaining. So you can see that Nash bargaining and posted lie our bracketing the social planner problem. Over here and the planner would also, this is by construction have the most teachers hired possible, which in this case is 120,000. So just giving an idea of what the consequences of collective bargaining and monopsony power could be in this market. There's one more interesting conclusion here that we hadn't realized before we started unpacking the model. When Gregor was talking about when there's equilibrium effects that you're not anticipating, we got one of them which is we were kind of thinking if you increase the wages of one school, does that increase the wages for other teachers through competition in the labor market? And in a model where we were always on the labor supply curve, I think that would be necessarily true. In this model what happens is that I raise the wage somewhere it both makes workers want to go to that school, but it also makes that school district hire a few people.

And those additional people that didn't get hired now are trying to get jobs at the neighboring schools. So you have this kind of interesting externality that wage increases can have positive or negative externalities on other schools. Likewise, it turns out that better bargaining parameters at one school, better collective bargaining might actually be better or worse for workers at other school districts. And so if you know the Ho and Lee paper, there's kind of these interesting kind of offsetting effects of equilibrium effects of bargaining in one place versus another. And that's it.

Speaker 4:

All right. We have time for questions.

Speaker 9:

Alan, so I guess when you were talking about it, my mind was going back to kind of Caroline Hoxby rivers and streams stuff. And to what extent have you thought about playing with the geographers of the school districts to think if we made school districts bigger or smaller, what is that doing to obviously wages, but also commute times and equilibrium in the model?

Allan Collard-Wexler:

Yeah, I think it's a great question. I mean even broader, the proposals having statewide bargaining versus not are kind of interesting. There's some issues with how you set up the objective function of school district when you combine them that we haven't figured out yet is slowing us down now.

Yanyou Chen:

Yep, excellent. Enjoy it very much. One quick question about do teachers move? So I think part of the result is driven by you have this exogenously fixed location of teachers.

Allan Collard-Wexler:

So the comment I was thinking about is during COVID a lot of people did remote work and they could move anywhere and so you got to see what their ideal location looked like. As an empirical matter I'm not exactly sure how you uncover my ideal location. I think it's tricky, but it doesn't mean some of the exogeneity of locations here is maybe trickier than we're saying.

Speaker 10:

Hi Alan, on your right.

Allan Collard-Wexler:

Oh, good. Hey.

Speaker 10:

I love this paper which will surprise no one. I have an unfair question outside your model. You might imagine that if we moved to a posted wage equilibrium you would get less long run entry into the teaching profession. So a little bit inside your data, at least if not inside your model, how binding is the constraint for school districts of running out of teachers to hire? Because that might inform how much we worry about those long run effects.

Allan Collard-Wexler:

We're going to need movement on the extensive margin so we're going to need more teachers than those that are just being employed right now otherwise mechanically we can never get that. And what we're doing is we're looking at who got certified to be a teacher and who was teaching previously, but is no longer teaching because they're also certified. Tezer may correct me on this one, but I think at this stage that really doesn't bind very much. There's enough people that quit teaching. When adding them over say 10 or 20 years, you have a large pool of excess teachers, but we haven't explored what are different assumptions you'd make on that just to see what would be better on that aspect.

Speaker 11:

Super interesting talk. There's this older literature on multi-unit bargaining that I think is often thinking if the UAW negotiates with Ford, and GM is a UAW shop that maybe disagreeing with Ford isn't so bad because everyone will stay in UAW, and if they're not maybe the UAW will really suffer. Do you have a sense of in this market there's a lot of shared unions across neighboring school districts or should we really think of these as independent unions?

Allan Collard-Wexler:

So we went through the collective bargaining agreements just to see the timing. So they're not negotiated at the same time. As you might expect they're represented by the same umbrella organizations. There's two points. So one is should care about other unions. So what is the objective payoff in the Nash bargaining of unions and can we play with that? I think that's where it happens. On your previous point, the Horn-Wolinsky paper that gets used for Nash-in-Nash bargaining actually also has a union paper published the same year. So that idea's been around for a while.

Speaker 4:

All right, one more question.

Speaker 12:

Hey, I was just curious about teacher quality, and since you have this very, very low number of offers that comes out of the estimation I think is there some sorting going on in school district on that front?

Allan Collard-Wexler:

Yeah. We have this movement not being correlated with rank. There's some other evidence in this literature about value added not being correlated with pay, but the idea that all employers are seeing something that I don't see that's not reflected in value added, I'm not sure what are the ways to either validate or disprove that, but that's the big outside explanation here.

Speaker 4:

All right. Thank you so much, Alan. We now will break for lunch which will be in the back corner there and we will resume at 1:00 P.M.

Sam Kleiner:

Okay, welcome back everyone. I hope everyone's well-fed and ready to go for the next session. My name's Sam Kleiner I'm a staff economist at the FTC and one of the co-organizers along with Viola. I wanted to take a few moments to reiterate our thanks to all of the folks who made this conference possible. It takes a lot of people doing work behind the scenes. So I wanted to first thank all the folks in BEU who helped us out with the selection and just the organizing duties. Also wanted to thank our two points of contact from the FTC event planners, Pinar Gezgec and Bruce Jennings who were the main points of contact for the production team. And I specifically want to call out Stephanie Aaron. Is Stephanie in the room somewhere?

If she's not, give her a shout-out if you see her. She's the one writing all the emails to you. I'm sure you've seen her name on the emails. She is I think the true of this conference who helped put everything together. She has amazing attention to detail with all aspects of the conference down to every last detail from the call to papers to checking all of the slides. There she is right there on the door. So she put everything together. So thank you, Stephanie. So with all that said, let's get back to some more research. This first paper is going to be presented by Andrey Simonov, the Gary Winnick and Martin Granoff Associate Professor of Business at Columbia Business School who's going to be presenting the paper, What Makes Players Pay: An Empirical Investigation of In-Game Lotteries. It's going to be discussed by Fabliha Ibnat, a staff economist at the FTC. So with that I give you Andrey.

Andrey Simonov:

All right. All right, thank you and thank you for having me. My name is Andrey, so I'm at Columbia University and this is joint work. The paper I'll present today will be joined to work with Tom Omana who is at HBS. In the paper we'll talk about video games. We'll talk about lotteries in video games and microtransactions not a topic that typically you seen this type of conferences, but I hope to convince you it's an interesting topic and there is a lot of things going on, and so for the next half an hour that will be part of my goal. So we'll talk about a particular type of microtransaction, it's a class of lotteries called loot boxes. What is it?

It's in game in your app, you are playing it and you can purchase an item which gives you a random reward. How is it different from other random features which might be in your video games or other entertainment goods? It's purchasable and it's standalone choice. It's like you are in the app and you can think about this, a casino which is in the app which will give you something useful potentially in the game. And where do we start in terms of the size? Economically why it might be important. It's a big market. Video games themselves, it's a big part of this market. We have some good data for 2020 around 10% of revenue in 2020 of video game companies came from loot boxes and more than half of the top 100 most earning mobile games also had them as a monetization mechanism.

So it's a big market. Now here is a typical example in FIFA Ultimate Team mode. You play the game, you open a lottery, sometimes you get good news, sometimes you get bad news. So here it was good news. So I think FIFA and Electronic Arts made more than a billion dollars of revenue at the same time. It's a big source of revenue for them. Now there is two different views on these lotteries. One view is that it's perfectly fine in terms of gaming. It's part of the game, it's part of the experience, it's voluntary, useful in the game, it's complementary in terms of the gameplay. It's a strategic dimension in the game of skill.

Here is a quote from the CEO of Electronic Arts who owns FIFA, "reflects the real world excitement and strategy of building managing the squad." That's one perspective. A different perspective is diametrically opposite. It's gambling that it's embedded for video game for kids. It's a lottery for real money for a price and then maybe there was some direct utility, but it also comes with some problem gambling features. Overspending, addiction, impulsive consumption, that's a different view. So you can imagine it got attention of regulators, but there is no consensus across jurisdictions. Some countries say it's banned and it's gambling, some countries say it's completely allowed.

In the U.S., in the UK and EU there was or are ongoing debates on what to do. In fact, FTC did a workshop on loot boxes five years ago, here in your case there was call for evidence, in EU there was a resolution recently and there was more things going on now. So there is a tension. Let me switch one useful jurisdiction to focus for this paper where this paper starts is the case of the Netherlands which first banned this type of products and then the highest court overruled saying that in FIFA this lottery, this loot box actually part of the product and should be allowed. Why? Because part of the game of skill they're strategic, good complementarity is important and they're used for game participation.

So this question is it a standalone product or is it part of the game? Is one of the risk couple of important features but one of the important aspects of these debates. That's really where this paper will start. We'll have a key study and I'll tell you about in a second, what is empirical framework? We'll have a key study. We'll try to understand what drives people demand for these lotteries. Is it the complementarity part? Is it this functional value? Or is it the direct utility which maybe will be respectable in terms of welfare and maybe will be driven by addiction? So we'll try to separate these two things out. In this type of products, it turns out that there is a group of players which everyone talks about and everyone will worry about which is labeled whales.

It's a video game presentation so I thought I'll do emojis as well. Why not? So this is a small fraction of players who anecdotally are responsible for most of the revenues. We want figure out how question one applies to this players in particular because that potentially is the most at risk. They spend a lot. Do they spend because they really enjoy the game and the complementarity or do they spend for other reasons? Finally, once we have those separation of tastes, we want to know what would be the implication of different policies you can impose on companies to regulate these products. Now that's the question. So what do we actually will do in the paper? I'll start with a simple toy model of how do we think about this complementarity versus direct value.

I'll then describe. We have a pretty unique data from a Japanese mobile puzzle game company. Ever since they have access to we have access to and it's unusual because typically companies wouldn't share this data so we were lucky partly with the magic of my co-author to convince them to give the data to us. I'll show you some model-free evidence, of where the sources of taste can come from. Then we'll need to use some of the machinery we see a lot in IO in economics of single agent dynamics. Why? Because these lotteries will give you items which we use in the future in the game. So we'll have to do a simple forward-looking model. I'll talk more about this. And then we'll characterize consumer tastes, try to evaluate different product design and run counterfactuals with different restrictions on loot boxes.

Okay, so that's where we're going with the paper. Now let me start with this toy model of how we'll think about these lotteries. Consider a consumer and she can make two choices. She can play a game, a binary choice, yes, no, and so you can open a loot box binary choice, yes, no as well. If she plays the game I cannot point, but I'll try to explain as well I can. If she plays the game it's equation one, she'll get utility alpha from play. If she wins she also gets beta. She enjoys winning, that's great. If she opens a loot box, she gets a direct taste gamma and has to pay some price in terms of just buying this product. Now at the same time, if she opens this lottery, this weekly increases your probability to win. Sometimes it's bad items, sometimes it's good items.

So this also makes you more likely to win. So these two different things will be the thing we'll try to separate out. The first part will be this functional value of loot boxes and that the complementarity we'll try to measure. In our case it's mainly this probability people will win and in our context there'll be no social interactions. You can think how you can extend it to social interaction as well. The second component will be this fixed or persistent preference for loot boxes is gamma, and then in general can have collectibles, direct taste, also can have habit formation, addiction and all the other things as well. So that's a reduced form parameter for a lot of things. So that's our simple model and what we'll try to separate out.

Okay. Now with this, let me talk a bit about the empirical context. There is a couple of core feature we need to go through and I'll try to keep it brief because there is a lot of different things I don't want to get too much into descriptions, but it's a free-to-play puzzle game. The type it's called Match 3 puzzle. So think about Candy Crush when you think about this game. It has a sequence of 173 levels which you have to go through sequentially. Once you are done you can play a lot of other stuff and you can repeat. The player as they go along will accumulate inventory of items which helps them to make progress. We'll call them divers, but think about it as some inventory of items, and there vertically differentiated. We'll call the quality component rarity.

Again, you can think about this as quality. For every stage people will choose four of these items from the inventory to try to complete the stage. They can accumulate these divers either through plane or through paying money and through loot boxes and one loot box costs around three and a half dollars and can be opened in any state of the game unless person is actively playing the stage, so it's not a particular part of moment of the game, and there is some volume discount to open 11 of them. Okay. So that's hopefully will give us enough context to see what comes next. Couple of pictures of visuals of how it looks. On the left is example of stage. That's where you connect three colors, attack your enemies. In the bottom you have these items which you chose to help you play the game.

This is not exactly how the game looks. We asked an artist to give it to us because we couldn't show you the actual game, but it's very typical. In the middle you have this progression stage to stage, and on the right have a loot box, this lottery which a person can decide to open. Notice that by Japanese regulation they're required to make probabilities of these different quality very visible. Now once a get to model, we'll assume people know these probabilities. We can have a discussion about what else we could do here. We'll assume people have rational expectations and no probabilities. Okay, so that's our context. We have complete access to data. As I mentioned, it's a two and a half million people.

We see actions of play, opening loot boxes, outcomes, inventories, the currency stock, a lot of different things. Basically the same thing as the company says. A couple of summary stats I'll highlight. It's a big table. So again I wish I could point, but the blue square on top gives you on average how many main stage, which is what we'll focus on people play, and average is 38. An average opens around eight rare loot boxes. This will be this loot boxes you pay for. You actually need to spend money either in-game currency or actual money to open. An average person gets to stage 18 and spends 78 of this game currency, five of them for a purchase. So five of these points is around three and a half dollars.

So an average person doesn't spend so much. What's really interesting is the extreme right tail of this is how much they spend and how much they play. Let me just highlight it on the next slide. These purchases are particularly concentrated. In this game 90% of revenues they get is coming from one and a half percent of players. This is very typical for this product where this is a guy's called Wales, that's where they get most money. The highest is one person spends 33,000 on this game overall and $3,000 in one session. And this game I think wasn't one of top 1000 games in Japan in a month so it is not the most popular game which is why we can get the data. The organic in-game currency expenditures and activity is much less concentrated. So the 90% of activity is done by 30% of players.

So those one and a half percent of players it's not like they play way more than everyone else, they just purchase a lot. And in this game 96% of money are spent on loot boxes. So that's the main way how they make money. A couple of more descriptives on this part. So one is, we start with two and a half million players, by last stage we have only around 40,000 players left. So there is a lot of attrition over time. You'll see that every four stages the probability to replay goes up. That's because this is by structure of the game it's hardest stages. If we look over time, the probability to win the game starts going down.

In the beginning it's around 96%, in the end it's around 50%. And again, every four rounds is this stage where it's harder to win. And on the same rounds where it's hard to win, people are more likely to open loot boxes. This correlational, we can call it elasticity, is around 1%. So just if we compare across this 170 rounds when they are more likely to lose they'll open it more. Hard to interpret because there is a lot of other things about design which might fit into this. The last thing I'll mention about descriptives is this is based on people who reached the final stage. If we compare these people who are this picture on top to everyone, to all two and a half million people, these probabilities look not very different.

And in the paper we go through different arguments for those. There should be selection on who other people who succeed and stay in the game. We don't see as much selection because people leave the game for a lot of other reasons. So for us, once we get to structural exercise, it'll be important. Think how selection feeds in our results. Just wanted to point out we don't see so much selection on people who stay in the game till the end in terms of the win probabilities and actions. Okay. Now before we get to a full kind of translating our toy model, taking our empirical context, putting them together in something more complex, let me show you a bit of model-free evidence on what to expect. Nice feature of a lot of these video games.

There is a lot of randomness which is built into the product, which in this case allows us to say something about the preferences. One thing I'll show on the slides here is that the loot box itself by definition is random. So sometimes you get good news, sometimes you get bad news. We can see if once you get good news or higher quality item, you are less likely to go and use the loot box more and now you'll go and play the game. Why? If it's functional value you should be more likely to go and to use this item and enjoy winning the game and progressing in the game more. Okay. So we'll do this model-free evidence with a simple IV regression. We'll look at the probability to open loot box after opening loot box right now. So open it again.

We'll instrument the quality of the inventory, this R, with the outcome of the loot box, which you just got, which we know is random. In this paper we'll summarize the quality of the inventory by the quality by rarity of top four items you have because you can choose up to four items when you play the stage. And then we include user fixed effects as well as stage by your inventory time T minus one is fixed effects. If there was no missing data measurement error we didn't need IV, we control inventory T minus one and just can do a less. Sometimes we have missing data so we'll also use IV for rarity. Okay. So we run this, what do we get? For regular players, non-whales, if they have a one x extra rarity item in the inventory, they're less likely to gamble again, to open the loot box again.

They're more likely to go and play the game. This effect if anything is stronger when we get to a higher quality inventory. So here column switch, did they have a bad inventory before, they have a good inventory before they opened? And in both cases they reduce the probability to open the loot box so it means they go and play more. This is the only actions allowed except for leaving the game. And if anything in effect is stronger because it's harder to get this one extra rarity point into the inventory. For whales results are very different. These guys don't care out if they've got good news or bad news, they can go and open it again. If we split by inventory we see a smaller effect if they have weak inventory and so it's closer to the beginning of the game they played.

We don't see any significant effects on the probability to open loot boxes last once they have good inventory stock. So that's some model-free evidence. There is a lot of other things we might not be capturing. These guys they are strategic, they build, they maybe accumulate this. There is different things might be going on. So from this we'll go and take our toy model and build the simplest possible single-agent dynamic model we can with this data. We'll think about consumer at stage S at time period T. And time periods here is not calendar time, but just a sequence of actions you make. People can make four discrete choices. Place the stage we're at that, open one loot box, open 11 loot boxes or quit the game forever.

That will be our terminal action. There is a bunch of stage variables we need to take into account. The stage inventory, your currency stock, was the current stage lost or not to see how well you're doing. Will include state dependence on the loot box opening partly to account for some potential addiction, partly to control for any heterogeneity we don't capture fully with some extensions with it and prices. And then utility of playing the game will be very similar to what you saw in the toy model alpha minus beta if you lost. So Q will be one if you lost the stage. To win the stage you'll have some underlying probability to win the stage and transition and continue in this game, but what's really important here is what's the quality of your inventory, what is that RIT like?

How much of these items you accumulated. So that's where opening a loot box, once you open it allows you to update that inventory and potentially get better items. If you open a loot box, if you have enough currency you don't pay anything. If you are out of currency you need to pay with real money. So that also will help us a bit to identify what's the coefficient price and how reactive people are to prices. Otherwise, from opening one loot box you'll get alpha which is this direct effect. And if you are out of currency you'll pay gamma which is the price plus the state dependent with simple first order mark state dependence parameter.

Andrey Simonov:

Simple first order, mark of state dependence parameter. So very similarly for 11 loot boxes we'll have similar structure. Again, a fixed effect and you need to pay the price plus the state dependence. Finally leaving the game, this will happen forever and once you are out will normalize your utility to zero. Okay, so that's our setup, relatively standard. So I'm going quickly through this.

Putting all this together, we have a player who will be making forward-looking choices to maximize the utility. With our state space and with the preferences we can write out a Bellman equation. If we know the last storm in equation eight, this boils down to a very simple static multinomial choice logit.

So in this case, because we have two and a half millions of decisions of players who when to exit the game, we can actually use CCP estimation with terminal action property pretty well. Because for different states in the game we'll observe what is the probability a person will leave and that helps us to approximate for what was their future expected value function going forward. We'll estimate the CCP of action zero. We'll express, we'll account for the state probability transitions to get the integral, and then we get to a standard linear equation to estimate the parameters of the model. Okay?

Then with these estimates, let me quickly summarize what we get in terms of the point estimates and I'll show you some decompositions. One is we get estimate for every stage that people play. That's just a fixed preference for how much you enjoy that stage. We do it separately for regular players and for whales. In this case, there is no other heterogeneity allowed in the paper. We also cluster people based on different moments to see how much we miss if we just approximate these two groups as having otherwise homogeneous preferences.

We get also the preferences for loot boxes, state dependence, payments and losing the game. Whales compared to regular preferences have stronger preferences for loot boxes, stronger state dependence. They don't care so much about price and they still care about losing, so they still want to succeed in the game.

Okay, so that's a raw parameters, maybe not as informative just to look at those. So let's use this now to decompose the utility and see how much for different types of players these products are part of the game, how much complementarity there is versus how much is direct utility. So in general, having the estimates, we can compute what the expected future utility for a player, which is expectation of playing the stage plus opening loot boxes, plus deciding to leave the game. That's our baseline component.

We can use the estimates to shut down different sources of tastes. We can remove an option to open these lotteries and just leave the option of playing the game. We can also allow to place the lotteries but shut down the transition probability which is responsible for complementarity. So we'll make your open a loot box, but your rarity doesn't increase. So you get new items, but the quality stays the same, and we can do the same with shutting down state dependence if we want to learn more about how it decomposes.

Okay, so what do we get? In the first two columns, I show the overall decomposition for regular players versus whales. A regular player gets around 90% of the expected utility from this complementarity. Whales get only 3%. There is two sources of where this difference is coming from. Part of it is just regular players care much more about the complementarity than whales. So for example, if we break it down to stage five, it's around four and a half times higher preference from the source for regular players than whales. There is also less functional value leading the game because there this rarity doesn't matter as much as it used to matter before.

Okay, so this is our first result that for some players the complementarity, which is a story about that it's two integrated products, it's important. For other players, it doesn't look as important so much. So second, what we can do with this is we can think about counterfactuals and one I'll show you is counterfactual on product design where we'll increase or decrease the difficulty of the game and see which players, how much revenue we get and how much engagement we get from players.

It's interesting because the current design of the game, it turns out nicely balances revenue. The company gets from whales, where they get most of the money from engagement, where they get from regular players. And so if you try to put a value on customers who wouldn't pay to the company right away, that's the one way you can do it. Why would you want to have non-paying customers? Because popularity of the game will allow you to promote it and to make it much easier to sell or to distribute among these paying players.

And so the final thing I wanted to show is now trying to decompose as different parts of utility into loot box and gameplay utility on the different constraints of what the firm does. So here we have welfare on the slide. Just for the record, welfare here means any utility we get in the model. This can be preferences which we think are respectable from welfare perspective or things like addiction. So we can try to correlationally remove some parts, but we don't have a good way to pin down one or another. So taking all of that preferences as surplus.

In the baseline under the current design, the firm gets around 7% of surplus. That's our revenues. Players overall get 6% of surplus from loot boxes and 68% from playing the game itself. For whales, which are in column C here, this is different. So they get around one third from loot box in terms of their surplus and two thirds from playing the game. So that's the first bars in these three pictures.

The second bar is if we put a full blanket ban on loot box without changing anything else about design. Then the consumer surplus, producer surplus goes down by definition, but consumer surplus goes down by 25% because of the complementarity. For these regular players, that's where this functional value comes in. That's why it will not be great.

We can put a ban on paid loot boxes and then regular players recover almost all of their surplus. And finally we can think about different counterfactuals where we put spending limits, which allows us to recover all surplus for regular players and more surplus for whales. So even if we put the spending caps at $100 per person, even this high spending players already get 84% of the surplus they got before. And it shows you how you can now think about these different other policy actions with these estimates.

Okay, so let me stop at this stage. So let me conclude. We started from this observation that a lot of the discussion around loot boxes, one of the important inputs into a decision of should we think of them as gambling or non-gambling comes down to whether we think it's an integral part of the game and this complementarity plays a role. Or, it's a game and also there was a casino which we just throw in there and people, kids now can play the casino.

So we could try to separate out this space in this particular context. We see that for most players this complementarity is an important component. So it's part of this "game of skill." For most high spending players, it doesn't seem like it's the case. They go there and they open the slot race for a lot of other reasons, but not for the complementarity. This is the way we're trying to measure it now. And then we saw some of the steps, how we can use this to talk about game design and how we can evaluate different policy actions. All I have, thanks so much.

Viola Chen:

Okay, thanks.

Speaker 13:

Oh, that's our [inaudible 03:04:08].

Viola Chen:

These are, yeah.

Speaker 13:

There's a lot. Do you guys have any questions about [inaudible 03:04:22]?

Viola Chen:

Great. Hi everyone, my name is Fabliha. I'm a staff economist here at the FTC Bureau of Economics and I want to thank the authors for writing and presenting this paper. It was very interesting and also incredibly relevant for some of the work we're doing at the FTC in trying to regulate loot boxes.

So I'll start with that, why this is a very useful paper from a consumer protection perspective. Regulating loot boxes is a relatively new consumer protection issues at the FTC. And a key challenge that we face when we're determining if a loot box system is unfair is determining both injury from loot boxes to players as well as any countervailing benefits to players from loot boxes. These are difficult things to estimate and they require understanding, in part, how players view and interact with loot boxes.

So this paper provides a very useful framework to start thinking about this question, as well as convincing empirical evidence for how whales and non-whales tastes for loot boxes might be split between both functional utility from gameplay complementarity, which from a consumer protection perspective I'm thinking of as a benefit, and direct utility for loot boxes as standalone lotteries, which I can think about as injury to the extent that this direct utility is driven from behavioral biases like self-control problems that are associated with gambling. So that's a very useful contribution of the paper from this perspective.

So with that said, I want to talk a little bit about the part of the paper that I found the most interesting, which was these policy counterfactuals where the authors determine various sources of consumer surplus and producer revenue under baseline conditions and compared them to various policy actions. And the authors concluded that the simulations showed that spending caps recovered the vast majority of the functional value of loot boxes while preventing the firm from profiting from the over-spenders. And this is shown in the far right graph.

I think in the paper, the $500 spending cap, the very far bar there, allowed players to recover a hundred percent of the surplus from playing the game, 99.9% of the surplus from opening loot boxes and firms recovered about 85% of the revenue. And I wanted to ask how we should be thinking about this overspending that the authors identify in the paper.

So this 15% of unrecovered revenue, should we be thinking about this as a correction for a market failure where there are costs that whales have been failing to internalize and subsequently imposing on themselves? So like a kind of negative intrapersonal or addiction externality as it's called in the literature. Has this been causing inefficiently high spending and leading to a deadweight loss? And if so, would it be a relevant policy goal to try to minimize any revenue associated with spending that provides whales with surplus from opening loot boxes?

So basically try to minimize that middle green bar completely or is that not quite the right way to think about it? Should we be thinking about that surplus from opening loot boxes a little differently since it might be driven by both normatively good or respectable preferences? In the paper, I think you mentioned entertainment value from the resolution of uncertainty mixed with the self-control problems that are associated with gambling. So I think some discussion about that would be useful from a policy perspective specifically because again, from a consumer protection perspective it's useful to try to think about what specifically is the harm that we're trying to minimize with these policy counterfactuals?

Other than that, I just had two other more minor questions about other components of the analysis. I'll skip the first one because the authors didn't really go into it in this particular presentation and it might be a bit too much detail. But I'll go back to the spending cap counterfactual. The authors note that this counterfactual is simulated in a stylized way where players are actually myopic regarding their budget restriction. So they don't anticipate that they'll hit a spending limit.

I'm wondering why this myopia didn't really affect players' ability to fully recover their play utility by reducing their utility from winning. So in that previous graph, that blue bar, I don't know if I can... Yeah, the blue bar, I would expect to be a bit lower for maybe some of the lower spending caps, but I see that it's about the same compared to baseline. I'm wondering why that is because if players are myopic, I would expect them to not be able to strategically time their loot box openings or take advantage of the nonlinear pricing of in-game currency in order to buy more loot boxes and open more loot boxes within that budget restriction.

I'll finish by just highlighting three other future research ideas that I think would be particularly useful for policy. I know that these are all beyond the scope of this particular paper, but these are some of the big questions we've been grappling with at the FTC as we try to think about how to regulate loot boxes.

So for one, it would be useful to understand the effect of confusing or unclear loot box odds disclosures on player behavior. Video game companies tend to argue that odds disclosures that may seem convoluted to the layperson are actually very understandable to a frequent player or a whale. But there's also anecdotal evidence that players have been confused and overspend because of that confusion. So this is a useful empirical question that would help guide policy.

The second question that would be interesting is investigating the effect of disclosing the average cost of obtaining a desired loot box prize on player behavior. As regulators, we're worried that players don't actually understand how much money they're going to ultimately need to spend in order to get a five-star character or the desired character. And regulators say that these average costs are actually very difficult to calculate because it's hard to define the average player. And there's complexity when you start thinking about the nonlinear pricing of in-game currencies. So again, another empirical question that would be useful.

And finally, it would be useful to understand differences in player behavior by age group. As the authors mentioned, a lot of these players are children and we believe that they're particularly susceptible to some of the harmful behaviors that can result from using loot boxes. So it would be useful to understand how they interact with loot boxes. But that's it and I want to thank the authors again for writing this paper. It's very interesting and very relevant for our work here. Thank you.

Viola:

We have time for a few questions.

Speaker 14:

It is really an interesting paper. I wonder in the counterfactual spending caps, that means the game developer will receive less revenue, right. If you're thinking this may reduce their ability to elevate on the game later on, that might hurt other players to enjoy the game. So I wonder how you think about that trade-off.

Andrey Simonov:

Yeah, no, that's a great question. So first of all, let me thank for the discussion. This was excellent. And we can also connect offline because I have other follow up questions about this. This is great. So on this question about... Yeah, so in the counterfactual we didn't allow them to make any adjustments so it's partial equilibrium because they'll adjust the game in some way, especially if we don't allow any paid loot boxes, then they probably wouldn't produce the game to begin with. So it's a good question how they'll adjust.

One thing I'll say about this product and this game, if you look at the activity over the four years that we have the data, there was a big spike in the first maybe 3, 6, 12 months and then sometimes they initially update, but by the end... It took another two or three or four years for them to discontinue it even though there were few players.

So I would think that even this, they are doing this game in one or one and a half year to recover as much costs as they invested to get some revenues. And then the marginal costs of just keeping the game are not very high and so they'll probably discontinue it either way. So I don't think it'll be big adjustment. Now if we put really a strong spending cap, that will be a different story because then it'll change how they do it. Thanks.

Speaker 15:

So full disclosure, I'm the parent of a ten-year-old and twelve-year-old boy so you had me at FIFA. I want to come back to the last bullet point. I mean I know you don't have, I suspect you don't have or you would've used them, demographics of the users explicitly, but there's things that you can easily imagine as correlates. Like school holidays versus non-school holidays might have a much bigger impact on school children than adults. I wonder if you played with that at all.

Andrey Simonov:

Yeah, that's great. So we did, not as successful as we were hoping we will. The only demographic in the data we observe is a breakdown by the operation system payment type, so iPhone, Android so it's not great. Using my course's knowledge, we try to think about school holidays and timing of the day where school ends, the school starts. I think in Japan there was regulation that if it's a minor who uses the phone, they cannot spend more than a hundred dollars per month. I'm not sure, but so we tried to look for these patterns. We didn't find as much. If there were ideas of how we can try to recover this would be great because we do have the timing data. We just don't know who those guys are. But yeah, thanks. That's great.

Speaker 16:

Yeah, so a really interesting paper. We went pretty fast through the structural model, so I am not sure I caught everything. But I was wondering, so in your model players, the whales who are addicts, know they're addicts and you could envision a quite likely scenario there's sort of multiple cells or internalities where addicts, they're not myopic, they're forward-looking but they don't internalize the addiction part, and whether this would matter for the results.

Andrey Simonov:

No, that's a great question. So yes, so we assume they fully... In some ways they assume they know all their preference. Everything is part of the utility, everything is part of the choice and they are forward-looking. I didn't talk about transition probabilities, but we think that they correctly anticipate the odds, the transition. So all of that, it's a more standard single agent dynamic model and estimation.

We tried to go more into this decomposing the welfare respectable preferences from other. We initially thought of state dependence as some proxy for this, but thinking more about the context, this repeated actions of lotteries, there can be a lot of functional reasons why if you didn't get what you want, you'll go and do it right away, right immediately.

So one thing actually we observe in the data which I can mention is that the repeated action on open another loot box, it takes on average like five or seven seconds to open one more of the lotteries. The action between the action of loot box and play or play versus play, even once people finish the play, then it's more like one minute. So there is this repeated openings which will be consistent with some addiction or impulsive consumption. They happen very quickly.

But then again, it's hard to interpret because maybe these things happen for functional reasons, not because they're addicted. Maybe, I know I need something else and I'll quickly click there. So in the paper we try to stay away from interpreting one way or another, but ideally, if we had some identification to separate it out would be great. And we're happy to talk more about this offline.

Viola:

All right, thank you so much, Andrey.

Andrey Simonov:

Thank you.

Viola:

And our next presenter is Mark Shepard. He will be presenting on adverse selection and unnatural monopoly in insurance markets.

Mark Shepard:

Thanks so much, Viola and thanks for having me at the conference. It's really a pleasure to be here. Thanks to the organizers for including us on the program. Let's see if I know this. This is joint work with Ed Kong who's an MD-PhD student at Harvard as well as my colleague, Tim Layden, who's now moved to University of Virginia.

This is a paper about how insurance markets go wrong. It's a new way that they go wrong. Insurance markets are funny, they're different than other markets and that will be part of the point of the paper is to explain a new mechanism that we'll call unnatural monopoly in insurance markets. And you'll see why I call it that hopefully as we go along.

So motivation, health insurance systems are increasingly using market-based programs for their design. So if you think about things like Medicare Advantage or Obamacare Exchanges or whole systems in countries like Israel, Switzerland, Germany, Netherlands, they use insurance markets to deliver health insurance, this critical social good to our citizens. They're subsidized, they're regulated, but they're markets and that's important to make insurance market competition work well. That's going to be very important for the welfare of society, but concerningly... So one key premise for markets to work well is robust insurer competition. You need enough players in the market for competition to work well. And most prior research on this topic typically assumes that the competition's either exogenous, so it's a fixed set of competitors and there's some market power there, or it goes to perfect competition and assumes that will be an outcome here.

In this paper we want to step back and ask something that's not been asked as much about what may determine competition as an equilibrium phenomenon. And it's a big concern. It's a big concern because there are a lot of markets, a lot of insurance markets, particularly health insurance markets in America, that are very concentrated. There are some examples listed on the slide that over 70% of insurance markets in a variety of health insurance settings are highly concentrated by standard metrics. And this is particularly severe in the Obamacare or Affordable Care Act marketplaces that were set up to cover the uninsured starting in 2014.

Here's data on the Obamacare markets from a couple of years ago showing the number of insurers participating in each market. And you can see across county markets, it shows the number of insurers, number of counties where there's one, two or three or more firms. And when the scale is one, two, three or more, you know you're going to be in trouble with very limited competition. In fact, at that time about half of counties comprising 20% of the population had just one or two competitors, monopoly or duopoly, and 24 whole states had three or fewer competitors.

What's the four firm ratio when there's only three firms? I'm not sure. I guess it's just the top three. It's the three firm concentration ratio. This is a problem. That's our basic point is that low competition is severe in many insurance contexts, but particularly in the Obamacare exchanges. And what explains this? It is a motivating fact. We wanted to understand why robust insurance competition is so difficult to sustain in many settings, particularly in the Affordable Care Act markets. And of course there are going to be some standard factors that are relevant here as well as in other settings, regulatory barriers to entry, fixed or sunk costs of entry, political factors that were particularly important in Obamacare. These are all important.

We want to though argue that there may be other complementary features, an additional feature that's been missed in prior literature and that we think is important and concerningly is a fundamental feature of insurance markets, and that's the classic market failure of adverse selection. So we're going to argue there's a connection between limited competition and adverse selection.

What is adverse selection? Classic insurance market failure. It's one of the key things that makes insurance markets different. It's the property that sicker people, those who are higher risk tend to have higher demand for various types of insurance. And there's asymmetric information or unpriced cost heterogeneity that leads to a variety of problems.

Now typically, adverse selection has been associated in classic work with a couple of things. First, it's with markets not functioning or market unraveling or sometimes it's called unraveling of trade. Think about the classic Akerlof-Lemons model. We can't get trade in used cars because there's asymmetric information and only low quality cars are sold. Okay, so that's one market failure.

Another classic market failure with adverse selection more associated with the Rothschild and Stiglitz classic model is about quality unraveling. So all firms degrade their quality to try to avoid high-risk. Consumers who again are unprofitable because we can't price discriminate to cover their higher costs.

We want to argue and ask whether there may be another market failure associated with adverse selection, which is that in some settings where quality is heavily regulated and trade is insured via mandates and subsidies, could adverse selection also be a barrier to robust firm entry and competition in these types of markets? And that's the basic argument of this paper.

We're going to argue for a mechanism by which adverse selection, classic market failure may lead to robust competition. It'll be a new implication relative to prior literature for what adverse selection can do as a barrier to robust entry. So how does this work? The goal of this paper is to teach you a concept. So let me summarize it on this slide and then I'll show you how we build it up in the model and the empirical work that we do going forward.

Well, here's the key insight. Think about a market, I'll give you a specific example in a little bit, in which firms are differentiated and they're competing on prices. So they've entered the market and they're competing in standard differentiated Bertrand style on prices. We're going to argue that adverse selection can create incentives for something that looks like a race to the bottom in prices.

Every firm has an incentive to strategically cut their price to attract differentially price-sensitive low-risk and therefore profitable consumers. That's straightforward. That's actually been pointed out in prior work. But what we are kind of noting here is that price, even with quality being regulated or fixed, price is a tool for cherry-picking. So just like in Rothschild and Stieglitz quality was a tool for cherry-picking certain people. Here price competition is a tool for cherry-picking.

And in one sense that's good, right? That gives firms incentives to compete prices way down, which benefits consumers. Lower markups that can offset problems with market power. But in another sense it can lead to too aggressive price competition in which we're competing zero- sum to steal healthy consumers and we might not be able to sustain enough players in the market.

So that's the argument that we're going to make is that when adverse selection is particularly strong, it can be hard to sustain the markups needed to support profitable entry by a large number of firms, sometimes even two firms, while still covering fixed costs of participating.

We're going to argue that this is analogous to the classic idea of natural monopoly due to fixed costs. We're going to show you in the math how both adverse election in price competition as well as fixed costs enter in a very similar way. They'll additively both deter entry in a kind of additive way, but the welfare economics are different. So whereas both fixed costs and adverse selection will push towards less competition, fixed cost is a real cost of more firms operating in the market. Whereas we'll argue that adverse selection is a coordination failure where firms are engaging in this cherry-picking game that's inefficient. And so it may be undesirable to have as little competition as we see. We will therefore call the term unnatural monopoly as opposed to natural monopoly.

We're also arguing this is analogous to a classic race to the bottom in quality as in the classic work by Rothschild and Stiglitz. But here for price, condition on quality, that's important because quality is often well regulated in insurance markets, price is often less regulated. And so our takeaway for policy will be that we need to think hard about not just quality regulation, but potentially also policies that limit or soften incentives for aggressive price competition in insurance markets.

That's something that we're going to argue we see happen in practice in variety of insurance markets, but the theory has not been well understood until now. But we will actually argue for a controversial policy and I will appreciate your pushback and questions as we get to Q&A, which is price floors may be motivated in some settings. Price floors, so a limit on price cutting that we will argue will actually sometimes allow the market to sustain more firms and lower prices because of this inefficient cherry-picking. So that's the argument of the paper.

What are we going to do in the talk? I'll walk through the model to flesh out that basic theoretical argument. I'll then give you descriptive evidence from a setting where we have data, good micro data that lets you uncover adverse selection. It's the Massachusetts health insurance exchange. I'll show you reduced form evidence on key elasticities from that exchange related to price competition in adverse selection.

And then we'll use that same setting to estimate a structural model using that Massachusetts market. And then I'll do counterfactuals. The counterfactuals will be of the form of varying the level of policies that are used to address adverse selection or soften price competition and show you what happens. And that will be the paper.

Okay, let me start with the model. I'll spend about half the remaining time on just explaining the key ideas of it because I think this is basically a conceptual paper. I want to contribute a new idea about how adverse selection plays out and then the application will then show you how it could be relevant.

Okay, I'll set up the model. I'll walk you through a simple example that will hopefully convey the key ideas. And then I'll briefly outline the general theory about how this would play out because we think it's good. The ideas go beyond just the simple model. Set up, we're thinking about insurance market where there's potential firms J, who engage in a stylized two-stage entry game. Obviously, the real world is dynamic. There's many other complexities, but this is a simple model that's been a workhorse in the IO literature to convey ideas, and that's what we're trying to do here.

In stage one, entry; firms simultaneously decide are we going to enter the game? Stage two, the entrants engage in standard Nash price competition. Each insurer will have a single fixed contract. They're differentiated. We're going to treat that as exogenous for the model, although I think it's something in extensions. We may want to think more about endogenous differentiation. But importantly, we want to think about general horizontal differentiation among firms.

So often in adverse selection papers, it's always been about quality. It's always been about a high-quality H plan and a low-quality L plan. And the high-quality plan gets screwed over by getting so many high-sick consumers. That's not what we're going to be about. We're going to be about plans that may be horizontally differentiated, and yet we're going to argue on things like, by the way, hospital networks, which will be the key example. So if you think about firms that differ on which specific providers they cover, that's a horizontal differentiation. Yet we're going to argue that adverse selection is still important.

Consumers will vary both in preferences as well as risks and costs. Firms or insurers will not be able to price discriminate against sick consumers. That's realistic based on regulations in insurance markets. Okay, so adverse selection in the model, firms are horizontally differentiated, or at least there's a mix of vertical and horizontal components and yet adverse selection is still relevant. That's going to be a key point of the paper. Why? Because the sick still care more about those horizontal attributes of quality relative to price than do the healthy.

So think about this. Imagine you had, this is a rough conceptual idea, utility for a different firm. For each firm J, for different consumers, is a function of QIJ. That's your match, how good you perceive, say the insurer's provider network to be based on where you live, minus price plus some epsilon IJ, consumers will differ in their willingness to pay for that match quality, what we're calling beta i here on this slide.

And importantly, we're going to argue that high cost consumers, sicker people care more about that quality metric. Why? It's pretty natural. If you're sick, you use the hospital more, you want a more convenient hospital network. If you're sick, you use benefits more. You want to make sure that your drugs are covered and so forth. So for a variety of reasons, it makes sense that often sicker people will have higher willingness to pay for quality and therefore, conversely, healthy people are more price sensitive in their demand. That's just the flip side of the same thing. The implication will be that-

Mark Shepard:

... flip side of the same thing. The implication will be this phenomenon that we're calling adverse selection and pricing. Even with fixed quality, what will happen, price cutting by a firm will differentially attract low-cost consumers. As a result, there's a wedge between the average cost of all my consumers as a firm, and the marginal cost of my consumers who come in when I cut prices, that will be relatively low. So average cost minus marginal cost, there'll be a positive wedge. There'll be a positive gap between those two. And similarly, if I raise my price, I'm likely to attract a higher average cost set of consumers or in quantity. As I expand my quantity, I move down a downward sloping cost curve.

Now one of the key points we want to make in the paper, is that that looks a lot like natural monopoly due to fixed costs. Here's just a simple textbook graph. On the left shows a textbook adverse selection market. On the right, a textbook natural monopoly market. You could find this in any Econ 101 textbook. And you'll notice there's a couple of parallels here. In both settings, there's downward sloping average cost curves. In both settings, there's a wedge between average and marginal costs. They're happening for different reasons. On the left, it's because if I as a firm cut my price, I bring in relatively low-cost marginal consumers. I'm moving down a downward sloping cost curve because of risk selection. On the right, it's because I have big fixed costs. And as I get more consumers, I spread those fixed costs over more people.

But in both cases you get this downward slope, you get this wedge, and those two things, maybe not surprisingly, will mean that both will behave similarly. Adverse selection, just like fixed costs in our classic theory, will serve as a reason why a market can support fewer firms than otherwise. And if it's very severe, if adverse selection is very severe, just like if it's fixed costs or extremely high, you may have something that looks like a natural monopoly unless you do something about it.

Okay, simple example to explain these concepts, if it's not clear from the graphs already. Think about a market where you've got two plans competing in a small city and the plans each exclusively cover one hospital in the city. There's East-Side hospital, West-Side hospital. We're going to assume that the firms are therefore horizontally differentiated, but symmetric in other respects. You could think about adding a vertical component. Maybe one firm could try to cover both hospitals, but here we're going to think about them being symmetrically differentiated. Consumers will vary in where they live in the city and in their health risk. This is very much like a hoteling model, but with risk added. And so you've got these healthy consumers who are smiling, these sick consumers who are blowing their nose, and they differ throughout where they live in the model, but they also differ in their preferences. They'll care about coverage of their nearby hospital but they'll also care about cheapness, about low price plans. And healthy versus sick will differ in their preferences for how much they care and their willingness to pay for that.

Now, let's see how equilibrium plays out. Imagine that firms set equal prices. That will be an equilibrium right there. Symmetric, so they probably should set symmetric prices. They both price around average costs, let's say. Then they'll split the market, consumers will go to their preferred firms. Everything will be kind of efficient and optimal. But what if a plan undercuts? Now here I'm showing the West-Side plan undercutting. They're going to steal consumers, but importantly they're going to differentially steal the healthy consumers who are more price-elastic. Their marginal consumers, therefore, are differentially low cost. That's the gap that we're talking about between low marginal costs compared to average costs.

But notice they still attract, even though they set a low price, they still attract their sick consumers on their side, so their average costs are still higher. And the East-Side plan, they still get some of their sick consumers who stick with them. They're now in trouble, right? Their price is is higher than their average cost. So they may want to fight back. The East-Side plan may want to fight back with lower prices. And again, they have low marginal cost consumers. And you could imagine this playing out. We're either going to equilibrate with lower markups and you'll sustain more firms with lower markups. Or if it's extreme enough, we're arguing that you may not be able to sustain both firms in the market. That's the logic of the model. And that would be bad because you would have both higher prices and loss plan variety for consumers. It would not be an optimal solution.

So, what could you do about this? The idea is that price competition is going wrong. And so you might want to step in to either soften the adverse selection incentives, so we'll talk about policies related to that, or you might want to limit the price competition. Another way of trying to solve the problems in a way that you could sustain easily two firms in the market and it could be better for consumers as well as allow more firms to participate. That's going to be the key argument.

Now, when does this play out, in general? You can write down the first order conditions for insurer pricing, conditional on participation. Standard price equals marginal cost plus a markup equal to the inverse semi-elasticity of demand. Very standard. Our point is that if you then ask what are the profit margins for firms in equilibrium? Their price minus average total cost will equal the Lerner markup, minus the wedge between average and marginal costs due to adverse selection, minus fixed costs per consumer. And this is the point that we're making in the paper, that both adverse election and fixed cost per consumers enter in a very similar way to the total net profit margins, which determines whether firms are willing to participate. So in both cases you're sort of getting lower markups, which therefore may lead fewer firms to be willing to participate.

And so prior work has thought about this with fixed participation. If you have a fixed set of firms, that's good for consumers, lower prices. But with endogenous participation, it may also limit how many firms are willing to compete. And it's really a horse race. It's a horse race between how big is the differentiation in the Lerner markups, which will tend to allow more firms to compete versus the sum of the entry-limiting forces of adverse selection and fixed costs. And when adverse selection gets very big, it may overwhelm the ability of insurers to differentiate and compete.

Okay, so our main point has been that adverse selection limits entry when insurers strategically compete on prices. But unlike fixed costs, this arises from a potentially inefficient coordination failure. More firms could enter if they didn't engage in the zero-sum price competition. And so there may be policy interventions that would be optimal. So we will evaluate policies that might soften price competition as a way to try to encourage more entry and ultimately, hopefully better results for consumers. That will be the idea that we'll simulate with our structural model.

The setting and descriptive evidence, we will boot the same setting in both brief descriptive evidence and the structural model, so let me give you a little bit of background about what we're studying. Our motivating case was the Obamacare or Affordable Care Act health insurance exchanges. There isn't as good data on those exchanges, certainly not the micro data you need to do adverse selection, in many cases. So we're going to draw on data that we have from Massachusetts Health Insurance Exchange where there's excellent micro data linked to health insurance claims and costs where you can test some of these theories around adverse selection.

The market, though, is very similar to Obamacare, with some key differences that we'll point out. But basically it's a health insurance market subsidized by the government with competition regulated and it's for poor individuals, for low-income adults who don't get coverage from other sources. It's heavily subsidized and ensures there are about four to five competing health plans in this market with standardized cost sharing, but the plans differ in their hospital networks, and so there is differentiation. It tends to be roughly horizontal, although I'll point out one plan that's significantly more narrow networks than the other ones.

One thing that's important to know about this market, is that even relative to the Affordable Care Act, there was more regulation in the Massachusetts Commonwealth Care Program than otherwise. Not only did they standardize plan designs, which they don't do in the ACA today, but they also had regulation on price competition via price ceilings and floors. They actually prevented insurers from cutting prices below floors that were binding in several years of the data. They also used incremental subsidies which were for the poorest people in the market. Those below the poverty line, all plans were free. And so in a sense, price competition incentives were very softened because half of your market, half of your consumer base doesn't pay prices. And so that price elasticity of demand is smaller in this market.

And what we're basically going to think about it in this case is, can we learn what the market would look like had some of these corrective policies, some of these adverse election softening policies, not been there? That's where we're going. And what we'll do is we will use these incremental subsidies as a nice natural experiment, a way of getting premium variation that's orthogonal to quality changes, as a way to get a sense of price elasticities and whether they vary for healthy versus sick consumers.

We will, just to be more specific, we'll use a difference-in-difference design that compares how demand changes for high and low income consumers, or relatively higher and lower income consumers in this market, where you can think about here's the five plans in the market over time. They vary their prices over time just due to normal price competition. And higher income consumers face those price changes. And we can see, okay, if a plan raises its price, does it get sicker consumers? Does its average cost go up? We can compare that against a control group of the below poverty enrollees who have the same plan menu but don't pay prices and that can net out any unobserved demand or cost shocks.

Here's, just briefly, the descriptive evidence. Here's our first stage. We're going to think about plans that raise their price at time zero versus those that lower their price at time zero. And it's all compared to that below poverty group as a control group that would net out any demand shocks. In practice, there's very little trends for the below poverty control group, so you can think of this as all coming, all the variation coming from the treatment group. Here's the premium changes. They're relatively small swings in premiums, but about $18 per month or 5% of average costs is your typical price change over time. We see in consumers enrolling every month at a monthly level, and what we can do is we can follow demand and see how it changes right at the month when prices change during the year.

Perhaps not surprisingly, on the left graph, firms that lower their premiums get more demand. Firms that raise their premiums get less demand and it's very elastic. This is a market with low income consumers. Each $10 increase in monthly premiums lowers insurer market shares by 10%, which is quite elastic. And then on the right graph is the evidence of adverse selection. Firms that increase their premiums in red get higher average costs. Consumers and those who lower their premiums get lower average cost consumers, consistent again with selection. This is not that they changed their products, they didn't change their networks, they didn't make other changes at this time. It's that they selected a given set of consumers and the adverse selection is quite strong. For each $10 premium increase, firms are selecting $11 per month higher average cost consumers. That's very strong adverse selection. That's consistent with there being very price sensitive consumers with differential price sensitivity for those healthy types.

This graph, this table just summarizes those difference-in-difference estimates, some of the same numbers, as well as heterogeneity across groups. Let me just point out that we can calculate that adverse selection wedge between average and marginal costs using our estimates. And in the first column one at the bottom, you see that it's about $110 per month, which is about 30% of average variable costs. So without policies that soften price competition or without risk adjustment in this market, there would be very strong price-cutting incentives that would, in a sense, overwhelm everything else.

Okay, so we are finding high price sensitivity and strong adverse selection, but Massachusetts was able to support more firms in the market than reality, than you might think based on those numbers alone. So what's going on? What we're arguing is that it's just showing the importance of those corrective policies that were in place, the incremental subsidies, the price floors, as well as the risk adjustment that the firms used. Did that allow the market to support more firms? That's the question we want to ask using our structural model.

And the key idea here, is we're doing the counterfactuals backwards from what we usually do. Usually we think about markets where something is broken and we're going to show you the counterfactual of adding policies in to make it work. Here we're thinking about a market that in some sense is working and we're going to show you what would be the effect of taking away those policies from the market. With our structural model, let me briefly overview what we do in the structural model, although most of this comes from prior work. We've drawn on past estimates I've done from prior papers on this market, and we're basically amalgamating those prior estimates into a single demand and cost system. Demand is multinomial logit. We're using our observed micro data to see how people choose among health plans. We'll have heterogeneity in price sensitivity coefficients by risk to capture that adverse selection. Cost comes from individual risk as well as plan-specific cost effects, so we can capture if certain plans are lower costs than others. We see a little bit of that, although mostly there's not a huge amount of variation there.

And then equilibrium, we're just going to put it into our two-stage entry game. Stage two is pricing conditional entry and stage one will be entrance among the set of firms who we saw in the Massachusetts market. Let me actually skip this in the interest of time. We fit the model pretty well in terms of when we simulate, use our model demand and cost estimates to simulate out those difference-in-differences plots that we showed you in the reduced form. We can fit those quite well. That's natural because we were basically fitting the model off of that type of variation, but it's comforting to see that you fit it well in sample.

What are we going to do in the counterfactuals? We're going to think about what happens if you take away some of these policies and we'll fit our two-stage entry game, I said that before. Just a couple additional details of what we do with the counterfactuals. Our potential entrance is always a concern in entry games. Who would be the firms who you think about would potentially enter off the equilibrium path? Here we're just going to keep it very simple. We're going to think about the existing firms in the Massachusetts market and we're going to take away some of those corrective policies. And we'll ask, do those firms still want to participate? It's, in a sense we're going to hold the characteristics of the firm's fixed as we saw them in the data. We're going to hold those identities constant and just ask do they want to enter in equilibrium?

We're not going to have any fixed costs in the model just for simplicity and conservatively we'll just keep those as zero. Obviously you add fixed costs as we do in robustness checks. It just reduces entry below what we'll see. And then monopoly pricing for, the monopolist is pretty unconstrained in pricing. So we're going to assume that the regulator puts a cap on prices in the monopolist case. And so that will just, in a sense, constrain prices below what the monopolist could have charged had they been undeterred. You can think this also might capture some type of entry deterrence or contestable markets kind of logic as well.

What do we find with the structural simulations? First thing, three quick findings. First, we find that if you take away those corrective policies, if you take away the incremental subsidies, the price floors and so forth, the market does unravel to monopoly. You can only get one firm surviving anytime and it's actually the lowest narrowest network firm. CeltiCare is the one that survives. They're the narrowest network firm. They're the ones that consumers like the least and they have the lowest cost structure. Whenever one additional firm tries to enter on top of CeltiCare, basically CeltiCare can out-compete them and steal the market entirely from them. That additional firm can't make money because it can't charge high enough markups to account for the fact that it's getting so many higher cost people.

Second, what if we bring in stronger risk adjustment? So the previous slide was saying, what if we take away all corrective policies? Let's gradually add that back in with risk adjustment, which is one key policy to address adverse selection. Risk adjustment basically taxes firms that attract healthier people and compensates firms that attract sicker people. We're flattening that average cost curve, making it less downward slope, weakening adverse selection. What do you see as you bring in stronger risk adjustment going from zero, no risk adjustment, to one being conceptually perfect risk adjustment? At some point you get more entry and the prices fall as a result and consumer surplus rises significantly, especially as you get away from that CeltiCare-only monopoly the consumers really do not like. The optimum is risk adjustment of about 0.8, which we find is quite a bit stronger. This is a conceptual simulation. It's quite a bit stronger than the actual risk adjustment that was used in the Massachusetts data, which was closer to about 0.3 or 0.4.

Finally, price floors, again the controversial policy, but it works pretty well and it's pretty simple to implement. If you set a price floor just above the market average cost, about 4% above it, you get three firms willing to participate. Consumer surplus jumps significantly, both because of lower prices and greater variety, but you don't want to go further than that. The optimum is actually to stick with that price floor just above the market average cost, basically as a guardrail against this type of adverse selection, cherry picking, inefficient price competition.

We also look at the two-way interaction of these two things and we find that the optimal policy... You don't need to read all the points on this grid. But the optimal policy involves moderate risk adjustment and moderate, modest price floors. You don't want to completely eliminate adverse selection because it induces firms to sacrifice their markups, which is good for consumers, but you don't want adverse selection to be too severe that you can't sustain firm entry and competition. You want it to be right in the middle for optimal consumer surplus.

Okay, concluding. Our main point has been to give you a new conceptual argument about how insurance markets can go wrong. That adverse selection can lead to limited entry and competition in insurance markets just like fixed costs. And we argue there's a symmetry between the two in terms of their implications for competition. And in the extreme case, the market can unravel the monopoly, but in less extreme cases you might just see less competition than you would otherwise. Price floors are a policy that we argue could be beneficial. They seem weird, but we actually see them in many settings including the Massachusetts exchange we studied. They occur in indirect ways in Medicare Advantage and Medicare Part D, and so they may be important policies to think about.

And finally, our overall idea here has been to give you a new framework for thinking about the role of adverse selection and endogenous competition in insurance markets. And to, in a sense, argue that insurance markets may be more fragile than we previously understood and that the managed part of competition that's really important for making insurance markets work may be very critical, not just for getting consumers to participate but also to get firms to be willing to enter and compete. Thanks very much.

Speaker 17:

And we have Andrew Ching to discuss.

Andrew Ching:

Thank you. [inaudible 03:50:00]. It looks like we have some appendix here too. First, thank you very much for having me and I really appreciate the opportunity of discussing this paper. This is a very interesting paper and thank you for assigning this to me. I have learnt a lot from reading it and it's so well-written that I am not really able to find little details thought that I can point out. And so my discussion is much more focusing on some thought about maybe what they can do in another paper. So keep that in mind.

Let me just recap the main ideas of the paper, which Mark has done an excellent job in presenting it. The paper is motivated by the observation that the ACA market, Obamacare market, is recently getting very concentrated and the authors ask why? And they propose that the explanation could be mainly due to the adverse selections of the market. And they use theoretical models to motivate, to explain, to make the point. In their theoretical models, they assume that firms or insurance providers, they do not have vertical differentiations, they only have horizontal differentiations, to make the point. And they show that in the market where you have some sicker patients, some healthier patients, and if the healthier patients are also more price sensitive... Actually, less price sensitive, then what you will see is that the firms, the insurers have incentive to price lower more aggressively, in order to attract those healthier patients because they are lower cost to treat and they're more price sensitive.

And now, this is a point that actually has been acknowledged and has been pointed out in some previous papers, that adverse selections can lead to more aggressive price competitions. But the authors push this further and argue that this fact, these implications could actually lead to a lower profit. And as a result in equilibrium, you might end up having fewer firms to be in the market because the profits are not enough to cover the fixed cost. And in some extreme cases, if the adverse selections issue is serious enough, you may see that there's only one insurance provider that can survive. And when that happens, that insurance survivor, that only survivor, is going to charge a monopoly price and that will lead to a very high price. And so the authors propose that to use a price floor, a very counter-intuitive idea, to correct this problem. And because the price floor is going to limit competition and that might actually lead to more firms in this market.

Now what I want to think about is, this is all good. I really enjoy, appreciate these ideas. But I want to just deviate from the theoretical models a bit and think about what if the insurance providers can vertically differentiate, in the sense that maybe one insurance provider will provide a better quality of care, another one provide less poor quality of care? Can you imagine, another way to compete is that one insurance provider will try to target the sicker patients, another one try to target the healthier patients, and they will use, they will contract hospitals with higher quality in order to target the sicker patients and vice versa.

And in that kind of situation, if the sorting is perfect, you can imagine that that will be an equilibrium outcome to where the adverse selection problems may not be too serious. And now, of course, in the real world we are never going to achieve these kind of perfect sorting. But to what degree that could happen? I think that's very much an empirical question. And in fact, when it comes to the empirical exercise, we'll see that in the Massachusetts market, there are insurance providers where they actually differentiated it in of the quality.

So when it comes to the empirical part of the paper, the authors are looking at the data from the Massachusetts set, and this is a really excellent data set and it has data that tracks individuals' healthcare utilizations and spending. And in this market, as Mark pointed out, there are a few insurance providers, and in fact they are differentiated in their networks. There's one that is smaller providers and provides smaller networks and they offer very competitive prices. And the premium can vary across the networks as well. And in this market, what you see is that, and in this exercise, what you see is Mark and his co-authors, the goal is to try to calibrate, use the data to calibrate or estimate the demand side parameters and the cost parameters of the model.

And this exercise is interesting, that in the modeling we have a macro paper. And this exercise I think in some sense is in the spirit, that you calibrate the parameters of the model and using the models that have problems, have the monopoly situations, but instead using this as an example to calibrate some parameters that are realistic and then simulate the factual exercise by removing those risk adjustment and price floor situations and see what happens.

Now, one key assumption about this exercise, is that the potential entrance network of hospitals and doctors are exogenously given. And they are given according to what you observe in the data. And now, following my thought about relaxing these assumptions and allowing for some vertical differentiations, one thing that you can imagine is that when you do counterfactual scenarios, change the price floor, change the risk adjustment subsidy, things like that, the insurance provider may also re-optimize and try to offer different types of hospital networks and doctors' networks. So it could potentially change the outcome as well.

Now, I'm not saying that in this paper the authors need to really explicitly do it, because obviously this is very challenging problem and it's a high dimensional optimization problem. It's very difficult to do. But perhaps one can impose some structures to the problem to simplify it. For example, maybe allowing for a few preset network configurations in order to address this. And I think I can share more thoughts with Mark.

And so now other detailed comments that I have about the monopoly situations that I think Mark pointed out earlier, one thing I'm wondering is to what degree that we actually see the market where we have monopoly, how high the prices really are? In the paper, I think at this point I haven't seen any figures that show that. And perhaps the authors can provide some evidence on this. And the one thing that they argue is that theoretically they don't expect, when it's a monopoly situation, they think it's going to stay that way and the price is going to be high. But if it turns out that the price is not as high as what the theoretical model predicts, I wonder could be happening, right?

One possibility is that maybe the threat of entry is disciplining the monopoly pricing. And the authors actually acknowledge this, but they argue that it's not going to be profitable for potential entrants to enter the market. But what I'm thinking is that, it is not entirely clear to me because theoretically, even though if a potential entrant sees that this is very profitable, and if they enter the market, they may have something like 50-50 odds that they can kick out the incumbent. And now, of course, the incumbent may actually have some absolute advantages. But still, if the profit is very high, it might still induce the potential entrant to try to enter the market, and in the sense that if the expected profit makes sense.

What could explain that? I don't know. But potentially it could be that, the potential entrants. We may not really know exactly what the demand is, looks like. And so in some sense if you don't price it too high, you might have preserve some of the [inaudible 03:59:46] information, and that could be one way to motivate why the monopoly market may not be pricing too high.

But anyway, these are some conjectures, and I have some other comments. I'd like to see more evidence that the adverse selection story could be really happening. And I do believe that this, to a large degree, it's going on in this market. But it would be nice to see that, for example, when you look across the market, is it the case that we see the more insurers in the market that we have more insurers, we have less patient heterogeneity in terms of their health status? That's a measure of how serious the adverse selection problem is. And on that hand, I also want to see some evidence about maybe potential sorting in equilibrium. And for example, when you look across the market, to what degree we see the insurance network differentiate among themselves in terms of high quality or low quality and so on and so forth.

And now I have natural questions that when I read the paper, it started off by using ACA to motivate this study. But at the end, when it comes to the empirical exercise, they used only the ComCare data, Massachusetts data, to calibrate the model, estimate the model. But Mark also pointed out that ACA data actually is not as detailed as the ComCare data. And so what I think the authors could do, is maybe use, discuss a bit more about to what degree other markets are similar to the ComCare market, the Massachusetts market? And to what degree they can argue [inaudible 04:01:34] that difference, how they can deviate the parameters a bit and say that the result is still robust, or how much confidence policymakers should have about those results.

And so to conclude, I think this is a great paper. I think it's a very interesting paper that generates new insight about the implications of adverse selections on firms' entry. And I learned a lot and I'm over time, so I'm just going to stop here. I encourage you to read this paper. It's really well-written. Thank you.

Mark Shepard:

Thank you so much Andrew, for those really helpful comments. And we've talked a little bit offline, but you're absolutely right that I think we are conveying insight here, but we need to do more work to say how relevant is this insight for what's happening in the ACA? And I took away that very clearly. Thank you so much. Other questions?

Speaker 16:

I had a question. So you are focusing on adverse selection on the intensive margin?

Mark Shepard:

Yes.

Speaker 16:

So if a plan lowers its premium, it's going to get healthy people, but they're all being stolen from the plan's rivals. I'm wondering if your conclusions would hold, do you think, if the concern is adverse selection on the extensive margin? There's uninsured people that the plan could get into the market by offering a lower premium. And in particular, I'm concerned if you have a price floor, that you may be preventing that type of selection if that's an important issue.

Mark Shepard:

Yeah, it's a great question. In practice in the ACA, you have what are called price link subsidies, which ensure that the extensive margin is in some sense shut down. For subsidized consumers, which are 90% of consumers, the post-subsidy price for at least one of the linked plans is fixed by law regardless of what intensive margin price competition happens. I think in practice because of that, it's a little bit of an interesting institution, but very important, most of the competition is on the intensive margin. That would be one response.

In general, though, when you do have extensive margin, what you're going to get is... We've done a little bit of simulation work with this. It can help a bit if you have some extensive margin, if you're competing against an outside option where they're not strategically pricing against you, and you can lower your prices to bring in healthier people to the market overall, the selection problems are less strong. But it's an empirical question, is that decrease in the amount of race to the bottom in price competition big enough? It'll depend on how that occurs empirically. We think it's less relevant to the ACA, but it could be relevant in other settings where there's a fixed subsidy of some kind.

Speaker 16:

Very cool. Because none of the costs are sunk in this model, it seems like this is actually a rare opportunity to talk about something we don't really talk about very much, which is predatory pricing and whether there's, if I'm competing against you as an insurer and we do the thing where we cut prices to cream skim or cherry-pick, and that gets us so far, and then maybe I want to go just a little bit further because I know that's going to actually put you out of business. This is actually one of the rare occasions where I could actually conceive of that actually happening.

Speaker 16:

... other occasions where I could actually conceive of that actually happening. I wonder if that's something that you capture and something that you maybe see evidence for in the data.

Mark Shepard:

It's a great question. In some sense, that's what's going on here. Because here, directly by competing, by lowering your prices, you're bringing in healthy people and you're raising your rivals average costs. There's a connection to predatory pricing in a certain sense, in terms of the theory. In terms of the data, that's a great question. I think one of the big unanswered question, if I take ... We're going with the question, is, how much do we see this actually playing out in the ACA markets? I think that's, for future work, something we should think more abou because we've given you theories from a lab in a sense, with our model and our Massachusetts data. I think there's questions about how much that's playing out in the ACA or whether there are other regulations in terms of insurance departments regulating prices. It may have stopped it there as well.

Speaker 18:

All right, thank you so much. I know there are more questions, but we are going to break. And so for those of you who do have more, you can chat then. We will reconvene at 2:50.

Ben:

I think we're going to get started pretty soon, so thank you everyone for coming back and hope you enjoyed your coffee. Up next, we are going to have a keynote address from Pinar Yildirim. Pinar is associate professor of marketing and economics at the Wharton School and a faculty research fellow in the Productivity, Innovation, and Entrepreneurship Program at the National Bureau of Economic Research. In her research, she studies media, technology and information economics, and she's going to be telling us about the effects of automation in the workplace. Pinar. [inaudible 04:07:00].

Pinar Yildirim:

Thank you. It's great to be here. I am, as Ben introduced, a researcher of technology. What I would like to talk to you about today, honoring the 30 minutes that I have, is the effects of, again, technology, thinking about the effects of technology in the workplace on labor markets. In some ways, this talk is going to tie to some of the discussions we were having in the morning regarding how people are moving across jobs, and in other ways I think it's going to potentially tie to some of the discussions that we are having and we will continue to have regarding the effects of, again, automation type technologies on various outcomes of interest. I don't need to probably motivate technology or the importance of studying the effects of technology. Technology has been impacting, shaping labor markets for a long, long time. But arguably, and you can push back on this, arguably, if you look at the technology that has been most importantly shaping labor force in the last two to three decades, that was potentially automation. And moving forward in the next decade, we can possibly see more of the influence of AI.

Now, what I would like to do in this presentation moving forward, again, is to discuss, focus on some of the effects of automation. What I want to do in particular, is to share some findings from a series of studies, different set of studies that we are actually carrying out with a set of co-authors right now, Maria Petrova, Gregor Schubert, and Bledi Taska, who was the chief economist at a company called Burning Glass Technologies, currently at SkyHive, who's going to be ... or major data provider. But moving forward to thinking about the effects of technology and automation, again, on labor force and in workplace. Now, again arguably, automation has been one of the most impactful sources in the last two decades shaping outcomes for labor. If you think about, of course, the number of studies that we have seen in the last decade in particular, that has grown exponentially with automation, many of those studies have focused on the possible dimensions of effects of automation that we can see.

One of those dimensions is a very immediate, very short-term effect displacement. You have a job and now you don't have it. There are other effects that are including wages that you might see, and there are of course many other effects of automation and technological changes that you might see as well. Some of those pertain to changes in the nature of the job, the task change. Some of those pertain to task allocation. But ultimately, one of the things that we argue is that many of these studies have been focusing on looking at the effects that you might observe on the immediate occupation that one holds. What has been less observed and perhaps should deserve more attention is the outcome that you might observe in the career consequences of an individual. The point that I want to make is that automation change or changes that are coming from automation does not only impact your immediate occupation, but it's potentially going to influence all the other occupations that you might hold in the future potentially because of the changes that you might observe in terms of the likelihood of transitioning from one occupation to another.

That might happen for a number of reasons. It might happen because the pipeline of experience, the requirements that we need for an occupation or the skill set that we need for an occupation, or the nature of the tasks that we observe on an occupation change. It might be for a number of different reasons, but ultimately the point is that we should probably pay attention to not just the immediate outcomes, but also a series of outcomes that we might observe in the long term. Now, so based on that observation or based on that claim, what I would like to do in this particular talk is, first of all, think about the effects of robotization in the labor markets on workers. Thinking about, again, this idea of careers, thinking about the potential implications for not just the immediate occupation, but for other occupations that people might be moving on to and understand that occupational mobility aspect.

Then I would like to decompose that a little further. And then I would like to also do a few other exercises that will tell me about how different individuals might be impacted by these changes differently. I will also highlight a few things that are at the individual level. In this talk, I will show a few individual level results that are going to, for example, focus on how an individual might be likely to be transitioning to certain occupations, or how likely they might be to go back to schooling. These are just some high level results that, hopefully, will be motivating or thinking.

Now, just to recap all of that. In terms of the research questions that we are going to high level focus on in this talk, we are doing a lot more in the papers. First, we'll ask this question. If you think about the potential career implications of technological change, how should we try to summarize those effects? How should we create a measure that will capture them? Two, is there an impact of robotization on the career values of individuals, the potential career path changes? And then three, of course looking into some of the heterogeneity in the potential changes that we observe. So that's the plan for today.

Now, how should we think about that very first question. How should we think about the value of holding a career? In this case, I'm going to abstract away from all the other benefits of holding an occupation. An occupation might give you different benefits. It might be of course quantifiable, it might be financial. It may be other things such as proximity to home. But we are going to think about an occupation as a financial measure, and we are going to think about potentially the stream of earnings, wages that an individual might hold if he could observe all the occupations that they could hold in their lifetime, we could simply discount some of these earnings, sum those up, and create, essentially, what seems like a financial value of a career for an individual.

Now, that's a very simple approximation, of course, but then we can think of the value of holding a particular occupation, O, at a particular time, T, at a particular place, C, by simply just expanding this idea that of course the benefit, the value of that occupation is the immediate wage that you earn, as well as all the potential other occupations that you can transition to, you can move to, and the future earnings that you might obtain from those occupations. So essentially, something that looks a little bit like a Bellman equation where, again, you're thinking about how much a particular occupation should be valued, and you're not only thinking about that by the immediate wage, but you're thinking about it by the potential occupations that you might transition into and the wages that you might get from those occupations.

Of course, here, if you wanted to do an approximation of the sort, a question that if you wanted to empirically do an approximation of this equation, a question that one has to ask is how do we think about the beliefs that individuals have or hold with regards to the transition probabilities that they have in the marketplace to different occupations, as well as the wages that they might hold in 3, 5, 10 years. Now, I'll tell you that even though of course individuals might hold much more sophisticated beliefs about how their probability to transition probabilities might evolve over time, how the wages might evolve over time, we are going to make an assumption here before going into the empirical approximation. We are going to make an assumption that in the absence of perfect foresight into how these parameters might change, the beliefs of an individual will be formed by their most recent observations.

In order to form an approximation, in order to form a belief about the career value that they have, they're going to use their most recent observations about the transitions that they observe in this particular market, as well as the wages that observe in this particular market at a particular time. Now, how do we think about approximating again? How do we try to get at potentially the career value of occupations that we have? In order to be able to get at a career value, we need two things. We need some approximation and empirical analog of the transition probabilities between different occupations, and of course we need some approximation, some data about the wages. Now, on the transition probabilities, that first piece, we are lucky to have a really nice data set that's coming from a company called Burning Glass Technologies. For those of you who haven't heard of Burning Glass, this is a company that essentially collects data about the labor market, they collect both data on job vacancies as well as on resumes.

And the data that we have is essentially data about 16 million individuals from the United States. For these individuals, we can observe their job history. So we know what kind of an occupation they hold, which company they worked at, when they started, when they ended this particular job. And then we also observe a number of different characteristics about these individuals. We know their education level, the number of years of schooling. We know their certifications, we know their gender, and we can approximate their age. And on top of that, we know their location at a zip code level. This gives us a great ability to approximate this transition matrix between different occupations. We have about 178 million sequential worker-year observations that we are going to use for that purpose.

Now, a question that you might see, or you might have in this particular setting is of course the representativeness of this particular [inaudible 04:18:02]. Naturally, the jobs that might require or the type of people who might carry out and post their resume in different boards, this is where Burning Glass is getting their data from, these might be white-collar jobs. And indeed, we are going to observe, we are going to have an overweighted sample that's mostly young, middle-aged workers who are in white-collar professions. We'll do a number of things to account for that. That's one disadvantage. Another question that we will have to deal with is this trade-off between precision of probabilities of transition that one has to calculate as well as trying to get at the heterogeneity across different subgroups when we're trying to calculate transitions. What I mean by that is that of course we can calculate, we have roughly in putting all these occupational titles to job classifications, luckily this was already classified for us, we have about a 700 times 700 matrix of occupational classes. So we are creating essentially a transition matrix of this sort.

You can calculate it with higher degrees of precision if you put all the data together. But if we wanted to really capture the differences across regions or across different subgroups in the population, we will have to just rely on the data from these subgroups or these different regions. We'll try to do both, but of course, keeping in mind the loss of precision that we are having when we make these decisions. But in order to be able to account for the differences across different regions in terms of the prevalence of a job, we are going to weigh the national transition matrix that we obtain by the prevalence of occupations that we observe in a particular region, region here being the commuting zone. We are doing this because we do not want to assume that a place, for example, that has no mining jobs, has the same probability of transitioning into a mining job as some other location that might have that transition, that might have the mining occupation.

For the wages, we are going to rely on the official data from the Bureau of Labor Statistics, occupational employment statistics data, and we are going to adjust that by inflation in order to be able to account for certain things. Again, I highlighted the caveat, the caveat that we are going to make the assumption that when calculating their career value changes, people are going to rely on the most recent observations from the last three years in terms of transitions, and they're going to look at the most recent wages in order to make an approximation into the future. But even with that caveat, we can actually generate some high-level highlights. First, let me show you how do the data translate into career values? How does that look like in the timeframe that we are focusing on? That's between 2000 and 2016. Of course, what we have right now is for over 700 occupations by the standard occupational classification code, a career value.

And we can generate that for every occupation, for every commuting zone, and for every particular timeframe that we are focusing on. But we can also just glean some high-level insights. Here, instead of the six-digit occupational code, I'm going to classify occupations at the two-digit occupational code, and you will see some occupation families. On the X-axis, you are seeing the starting salary, starting wages of these occupations at the two-digit level. And on the Y-axis, you are seeing the change in the career value in the timeframe that we are focusing on. You can see here already that there are some occupations that are starting at a fairly good wage and ending up in terms of improving their career values, which means these occupations have a good chance to transition into other well-paying occupations, and there are some occupations that start potentially at a low annual wage, but seem to improve.

For example, looking at the right-hand corner, management seems to be one occupation, class occupation family that seems to start fairly at a high wage and seems to be improving on the career value. If you look at fishing, farming, forestry, again, the lower end, the left-hand of the wages, you will see that it's one of those families of occupations that start fairly worse off in terms of wages, but seems to be improving in career values at the end of this time period. So it seems like, again, moving into better-paying occupations from this family, seems to be fairly high.

Now, I would like to also, just as a descriptive, I would like to show how in the same timeframe the starting wages compare to, again, the changes in the wages that one might observe in this timeframe. So how much of this, put differently, is coming from potentially the weight changes? And unfortunately I cannot ... Here, I can go back. I just want to show you, again, going back and forth, how flat, how much more, essentially, squeezed the distribution of these data points are when we just look at the changes in wages. So there's something else going on, and that seems to be essentially about occupational transition probabilities that seem to be moving the career values.

With that insight, I would like to move on to understanding how much of the changes in career values that we observe might be coming from robotization. What we are going to do is to run a set of regressions that are going to look like the following. We will try to get a measure of robotization, the change in robotization that takes place in the time period of interest that we are looking at, and we'll look at a set of outcomes. In the paper, we are looking at a much wider set of outcomes, but for this particular talk, I'm going to focus on essentially an aggregate measure of the career values in a particular location.

We can generate many different versions of this. But what I would like to understand is if we can focus on a commuting zone, a region at a particular time, and if we could think of all the potential occupations that are prevalent in this particular place, what does the weighted career values look like in this place. And if we can, look at two different time points. Do we see a change, do we see an improvement, or do we see a decline in the career values of these regions? And then we are going to try to understand, we are going to try to decompose how much of this is coming from robotization.

On the left-hand side, we can do an approximation through the labor market shares. That's something easy to, I think, go to. But on the right-hand side, we need essentially an exposure to robot measure that we can plug in. Now here, in order to get to the robot exposure, we are not going to try to reinvent the wheel. There are already plenty of studies that are trying to get an approximation of the exposure to robots. But in a nutshell, what we are going to try to do here is to follow a paper, a series of papers by Acemoglu and Restrepo, and others, and understand how the number of robots that are in use in United States changed relative to the labor shares in those industries, respective industries, calculate essentially this exposure, then weight it by the prevalence of those industries in a particular region. And think of that as a robot exposure measure. Of course, you are all going to object to this, thinking that there are so many correlated unobservables that are going to determine both the labor market shares as well as the robot adoption in these regions.

And because of that, what Acemoglu and Restrepo do, and what we are also going to do, is to instrument the robot exposure measures on the European robot adoption measures. The idea behind this is the following. Again, if there is no direct relationship from let's say Sweden's robot adoption to a particular region's robot adoption characteristics, the only reason why the robot adoption characteristics of this country could predict the U.S. robot adoption prediction should be about the technological growth. There should be some technological factors that can predict the growth of robots in one country relative to the other. Now, there could be some alternate explanations here. Some, for example, might relate to what about the trade, the export/imports that might be related to a country. And there might be other things. We could say, well, there might be other technological advancements like the IT capitalization growth that could also potentially create some correlation between these measures.

And without saying, without going into too many details, we can say that we are going to rule out these two potential alternative explanations. It was also ruled out in the original paper by Acemoglu and Restrepo. And we are going to use data from International Federation of Robotics. This is an organization that collects data about the robots that are in use by different countries. They have data about 50 different countries, and we are going to focus on the European countries and for a period of 2004 and beyond, where they actually start to indicate which industries these robots are used and installed in. Okay. Let me show you a few of the results. What I want to understand again, is how the exposure to robotization influenced the value of careers, and if we can approximate the value of careers, the aggregate value of careers in a region, how those careers were influenced.

What I'm showing you here on the first three columns, these are just OLS, and on the right three columns, you are seeing the European robot adoption instrumented versions of this specification. What you can see in general by focusing on columns four, five, six, three rows for three different time periods, we can see generally a negative impact of exposure to robots on, again, the weighted value of the careers in a particular commuting zone. Just to quantify these effects, focusing on maybe column six, how to read these numbers. They're of course just to highlight in 10 thousands. With one additional robot per thousand workers, the average decline on the career value is about $3,300, $3,400. Now you might say, "Well, this doesn't seem like a high number." Based on the 2,000 years approximation of career values of the average individual, this is about 1.5%. And of course, we see a lot of variation in terms of robot exposure throughout United States.

Some regions are exposed very little. The exposure would be about 0.2 per thousand workers. In other regions we see a lot higher exposure, so it would be about up to nine robots per thousand workers. You can see that for some regions, the potential effects of robotization will be much greater than others. Now, a question here is to understand what the effects of this robotization might look like. On the one hand, you could say, "Well, robotization might imply maybe getting rid of some of the careers." It's possible that some occupations are becoming obsolete in a region, so the composition of the occupations or the composition of the labor market shares could look different. On the other hand, it could be that maybe there's nothing changing. It's still the same occupations that are available in a region. Nothing is changing in the composition, but these occupations now have less availability to move to better paying occupations altogether. We could decompose the changes and the local market career values into a composition change effect as well as a career value change effect. Of course, that could also be the interaction of the two terms.

Now, another form of decomposition that we can follow, let's assume now that we observe some change in a particular occupation's career value that could potentially come from the wages. It could be that nothing is changing about the occupation mobility aspect of this occupation. You're still able to move to other occupations. That could be essentially the second term there, something about the wages are changing. Or it could be that nothing about the potential expected wages in this occupation is changing, but now you are going to be less likely or more likely to move to other occupations. Something about the transition probabilities are changing. We also want to understand if we observe some changes in the career values, how much of that can be attributed to the wage changes, and how much of that can be attributed to the career path changes.

In this table, in the next table, I would like to decompose, again, first into the composition effect and the career value effect. And then in columns three and four, I'm going to separate the career value effect into a wage and career path effect. The first thing you can see, focusing on, again, columns one and two. It doesn't seem like, at least in a timeframe that we are focusing on, the occupations that are available in regions are changing in a dramatic way. It doesn't seem like the occupations, again, are going away, or we are seeing more of the occupations in some regions relative to others. But what we are seeing is majority of the decline that we observed due to robotization seem to be coming from indeed the career value changes of the existing occupations. And here, if we go further in columns three and four and decompose this career value change into wage changes and career path changes, the changes in occupational mobility, we can also quantify how much of the change is coming from these two sources, about two-thirds of the effect.

A bigger part of the effect is actually coming from wages, wage changes, but at the same time, a non-trivial part of the change is coming from also the loss of occupational mobility or the ability to move to better paying occupations. So there's a reduced upward transition likelihood, and that's the part that we would like to focus on because that's the part that has not been very well studied. Decomposing these effects into high manufacturing and low manufacturing commuting zones, splitting by the median, we're actually starting to see that majority of the effects are actually coming from high commuting zones, high manufacturing commuting zones. For the low manufacturing commuting zones, of course our instrument is also getting weaker. We try different sets of European countries to get better F stats in other versions than the one that I present. But the same relationship holds in general that we don't see these effects actually reflect onto the low manufacturing commuting zones.

Put differently, the negative effects of robotization on the local career market values are concentrated in these regions that are heavily focused on, or the labor market is heavily focused on manufacturing. Now, I want to then go into decomposing, again, thinking about the effects of these transitions for different groups and for different types of occupations. The one thing we can look at is how do people move If we just think of the different wage categories and classify those as moving to essentially a higher paying occupation, roughly similar paying occupation, and a lower paying occupation. How do the occupational transitions look like? You will see in the first three columns that as robotization exposure in a region increases, the transitions are mostly to similar horizontal equal paying occupations or to essentially lower paying occupations. There are fewer transitions to high-wage occupations. And again, most of these effects, looking at the next set of columns, four/five comparison, six/seven comparison, and eight/nine comparison, most of the effects that we are observing are coming from the high manufacturing commuting zones.

We can decompose again in different ways. This time I'm going to focus on the effects, looking at transitions to other titles, other jobs within the own occupation category. So the occupational classes, again, about 700, 800 of them exist, and they are holding many different titles of jobs. So you could be moving even within the same firm to a different job that's under the same occupational class. At the same time, you could be moving to other occupations within the same firm or across different firms. So in the first set of columns, in the first four columns, we are going to look at movements within the own occupation that an individual is already holding.

And in the next set of columns, we'll look at transitions to other occupations different than the one is holding. And we'll try to understand how much of the effects of robotization are coming from the first versus the other. The effects are quite comparable in many ways, but a little more pronounced if you were to compare columns one and five, more pronounced for moments movements to other occupations. So it seems like especially when you're trying to move across occupations, there seems to be more adverse effects of robotization in a region. What other things can we say? So looking at individual level outcomes, promotions to management occupations, we generally see a negative association between higher degrees of robotization and the likelihood that an individual is going to be moving to a management type occupation by 2016, by the end of the period. Years of education doesn't seem to generally impact this relationship.

And years in production, if you were to just look at starting in a production occupation that seems to have a negative association, and one thing, one might think is maybe the skill set, maybe the sort of education or other certification, the experience that an individual has that shapes into various set of skills. Baseline skills, these are typically the skills like analytical thinking, communication that you would label in a resume, versus more specialized skills that are industry specific. You might think that maybe some of these characteristics might help to mitigate the effects of negative effects of being able to move to a better occupation. In the case of management, that doesn't seem to be the case. Looking at gender decomposition. So here in panels A and B, I am doing the decomposition that I have shown, this time just doing a subpopulation transition matrices, where we look at the transition matrices only for female and only for male individuals.

And as you can see, again, both males and females focusing on column two, they are negatively impacted, but especially on the dimension of occupational path reduction, males tend to be more negatively impacted. So that's another reason why it's important to focus on the occupational transitions because it is simply showing a greater difference than we look at the subpopulations. And why might that be the case? Of course, at least looking at automation in manufacturing, males are more likely to be holding these type of occupations, at least in the time period that we are focusing on. Another question and another sort of ability to look at this data is comparing people with different experience levels. So we can now create transition matrices looking at people with less than five years of education, five to six to 10 years of education and more, which we do categorize even more experienced individuals.

For the more experienced individuals beyond 10 years, the numbers look very similar to 6 to 10. I just want to show you this very junior, as well as the next level of seniority individuals and their comparison. Here again, it seems like the numbers are similar, but especially when you look at the occupational career path effects differences, focusing on column four, you see that individuals who have a medium level of experience, 6 to 10, they seem to be more negatively impacted. This might be possibly because the type of occupations that they're going to move to are potentially more limited, and therefore they see harder times transitioning to those occupations.

One last thing I want to show before concluding. Another question that we might have, again, looking at individual transitions. Well, maybe they are not transitioning to other occupations, other jobs, but maybe they are transitioning to going back to school. Maybe they're going back and investing into another level of education. Even though we don't see a clear path, clear relationship between the robotic exposure and investment in what I call reskilling, getting another-

Pinar Yildirim:

... exposure and investment in what I call reskilling, getting another degree. That could be a different type of degree for different individuals. Even though we don't see this clear relationship between the two, we can say a few other things. So years of education, of course, if you're already quite educated, you might not want to go back to school or you may have fewer options to advance your education. If I already have a doctoral degree, perhaps it's harder to get another doctoral degree. Years in production, in general, have a negative association with the degree to which you might be going back to school to get another degree. These two, higher exposure to robots, and again, the more experience, being more experienced in a production type occupation seem to have a negative interaction, which means the likelihood of going back to schooling to get another degree or another training to get back to the labor force is going to be less likely for these individuals.

At the same time, we look at skill characteristics and the tendency to go back to again school to be able to get maybe another degree. We are seeing just the baseline skills, as well as the specialized skills. These individuals, of course, the ones who already are perhaps skilled, they have an easier time going back to school, but the interactions are not necessarily always positive, at least we don't see an interaction for the baseline skills, and we see essentially a positive interaction for specialized skills. So it might take the few very highly specialized individuals to be able to go back to school to perhaps shield themselves from the negative effects of automation. But that's where I want to end things. I think I'm, in terms of the time, already at the end of it.

So, summary of the findings. Again, in the studies we have a lot more where we show the effects of these changes in local market career values on a number of different outcomes in terms of spending, in terms of investment in housing, in terms of the creation of jobs and business establishments and their employment characteristics, but what I would like to argue in this paper is a particular aspect of automation, robotization or technological change that has been fairly less focused on in the literature is the idea of looking at occupational transitions, how likely are these occupational transitions to survive and how do they change and how do they change for different individuals. That's fairly less studied.

In this study, we are trying to tackle essentially that question and we are able to demonstrate the effect of, again, robotization on the local market career values. We're able to decompose that into wage effects and occupational mobility effects. A few interesting things that are coming in. Again, more senior individuals and males seem to be more negatively impacted, especially focusing on this occupational mobility aspect. If we were to think of, again, promotions to management roles and educational transitions, we also see potentially some negative impact of robotization here in these key outcomes that we might want to focus on as well. With that, I'm going to conclude my talk. If you have any comments and questions that are going beyond this presentation, here is my email. Would love to hear from you. Thank you.

Speaker 19:

We do have time for a couple questions.

Speaker 21:

Have you looked at geographic mobility at all?

Pinar Yildirim:

Yes. So, two things that I didn't mention, one is migration patterns and another thing, unemployment, movements to unemployment. We do look at both. There are very few migration patterns when we think about especially who is impacted by robotization. There are some occupations that are potentially impacted by technology. For example, computer science type of occupations, these people tend to move a lot across jobs and there's some mobility within these individuals as well. But for the type of occupations where we think of manufacturing, it doesn't seem to be at least the case, not a huge mobility. Of course, people might be moving within the commuting zone, which is fairly large in terms of geography anyway, but across states, for example, or across commuting zones, that's mobility is a lot more limited. The second thing, of course, is related to that unemployment aspects. We do have all the regressions also with unemployment, and qualitatively there isn't a change. Quantitatively, of course, the magnitudes look a little different. Yeah.

Speaker 19:

Anyone else?

Speaker 20:

Very interesting work. I may have just missed this, but it seemed like the model you're looking at is changes in robotization having changes on wages, but if robotization itself has time to have an effect, then the stock might matter as well. Do you have a sense of if it does or if it really is the short-term shape?

Pinar Yildirim:

Stock as in the robot stock?

Speaker 20:

Yeah, exactly. If there was robotization 10 years ago, maybe it takes time to have a wage effect.

Pinar Yildirim:

There are two different measures in when we look at the Industrial Federation of Robotics data, one is about the robots and stock and one is about robots in operation, and one can potentially disentangle those effects. Looking at those in stock and in operation, in general, whatever is in operation seem to be quite correlated with whatever is in stock. So there might be delayed effects regardless of that. There might be delayed effects in terms of wages or in terms of being able to observe occupational mobility.

We are restrained with the data in terms of the timeframe that we are able to observe. But even in that fairly short timeframe, we are able to observe some negative effects both on the wages, as well as on the transition matrices that we are constructing. So long term, well, hopefully us or somebody else can replicate some of these and see if anything is changing.

Speaker 19:

All right. Thank you.

Pinar Yildirim:

Thank you.

Speaker 19:

We're going to take a quick break before our last paper session and we will resume at 3:50.

Speaker 22:

... have Malika Korganbekova from Chicago Booth presenting Balancing User Privacy and Personalization.

Malika Korganbekova:

Hi, everyone. Thank you so much for including my paper in the program. Oh, oops, sorry. This is a joint work with my fantastic co-author, Cole Zuber. Disclosure, Cole was at Wayfair when we were writing this paper, but he's an affiliate for the research purposes because the paper was written under the research agreement with Northwestern University. So let me motivate the project. Many platforms, they personalize user content. So for example, platforms like YouTube, Twitter, Facebook, TikTok, they may personalize advertising, and retail platforms like Amazon or Wayfair may show personalized prices. But all of these platforms, they also personalize the actual content, the products that are shown on their premises, which is exactly the focus of my paper.

So just to give you an example, imagine you go on a retailer's website and you're looking for a particular style or color of furniture. Then the next time you arrive on the platform, the platform will make the other similar products more prominent on the website. On the one hand, it is very nice that the platform would be trying to show you that something that they think you will like, but at the same time, if we stop and think what makes personalization possible, it is online tracking, right? So when you browse online, very detailed individual level data is being collected to power this personalization algorithms. So this started raising regulatory concerns over user privacy.

First of all, there is a general privacy concern where as consumers we might not know what kind of data is being collected and how this data is being used by the platforms. So there is this issue of data use transparency. Then there is a second problem which is more personalization specific because if you look at the regulatory reports, a lot of regulators a priori are kind of negative towards personalization and the reports usually state something like, "Personalization is harmful because it is manipulating consumer choices when consumers are not aware of that." As a result of this regulatory concerns, browsers such as Safari and Chrome started limiting online consumer tracking. So what that means is that the platforms are no longer able to collect user data within and across websites, or what I'm talking about here is that first and third-party cookies are being blocked by these browsers.

In this regards, the research questions that I'm asking are the following. First of all, is it true that personalization hurts consumers and maybe sellers on the platform? Basically, are regulatory concerns justified? I will show you experimental evidence that suggests that actually personalization helps consumers and smaller sellers on the platform. Then the next question becomes how will privacy restrictions that limit the ability of the platform to personalize impact different types of consumers, sellers, and the platform? I will show you evidence that suggests that privacy restrictions will primarily hurt more price-responsive consumers and smaller sellers on the platform. Even if we start accounting for consumers privacy evaluations, still consumers will be negatively affected by the privacy regulation. Finally, in the last part of the paper, I start thinking what can platform do to mitigate the losses from privacy regulation.

In terms of methodology, to answer the first question about the impact of personalization, I use a two-year long field experiment that I ran together with Wayfair, where we randomly turned off personalization for a sample of consumers on the website. So this field experiment allows me to make causal statements about the impact of personalization. Then in the second part, to understand the impact of privacy regulations, because a lot of this privacy rules are just coming up, they're all in the future, so what I will do is the following. I will retrain the platform's actual personalization algorithm using lower quality data to mimic different types of regulations that are in the discussion right now. Afterwards, I will simulate how consumers respond to the counterfactual recommendations that would have been generated under lower quality data environment using the structural model of search. Finally, in the last part of the paper I propose a simple probabilistic identity recognition algorithm that can help platforms recognize consumers in a probabilistic way even when the platform is not sure who the consumer is exactly. Again, I will evaluate the probabilistic algorithm using the structural model of search.

So this is a research question. Now I want to talk about the empirical setting. For this project, I partner with Wayfair. It's a large online marketplace based in Boston. One of the reasons, so Wayfair personalizes product ranking pages because they want to... In general, the idea is to show something that consumers might potentially like. So I'm sure a lot of you have seen this type of product ranking pages. So what personalization means here is the following. So imagine there is a consumer who was previously browsing for blue chairs. Then the next time the consumer arrives on the platform, the platform will show other blue chairs more prominently, so basically higher up on the ranking page results. Similarly, if the consumer was interested in white chairs, then they would see more of white chairs. Oh, by the way, this is a very trivial example. In general, personalization algorithms are very much multi-attribute based. So if they were looking for blue expensive chairs and they would see more of blue expensive chairs.

The way platform operationalizes this algorithm is as follows. So the input to the algorithm is this individual level sequence of clicks, add to carts and purchases that consumers make on the website. So it is an individual level data and it gets fed into this deep learning based algorithm. The algorithm's job is to understand the similarities between products, the similarities between consumers and output personalized set of recommendations, personalized set of rankings for each individual consumer. As you can see, obviously, a very important part of this process is the quality of the input data.

One of the struggles that Wayfair and many other platforms have is that usually if the items that they're selling is a big ticket item, then consumers would arrive for multiple sessions. They would use multiple devices, multiple browsers, and it is very hard for the platforms to connect all these sessions+ to get a full history of individual browsing behavior. It is super easy to connect user sessions if consumers log in voluntarily or are deterministically matched. But in the data, only 40% of consumers log in voluntarily, which means that the remaining 60% of consumers are recognized using online tracking technologies such as first and third-party cookies, and so this is exactly where the privacy regulation is going to be super important for the platforms.

In terms of the data, I have full access to Wayfair's data where what I observe is the device and the browsers that consumers use when they arrive on the platform. I know the source of traffic, meaning whether their consumers arrive directly to Wayfair.com or did they arrive from advertising channel. I know the product rankings that are shown at each consumer page load. Wayfair collects very detailed pixel-level click stream data, which means that all history of consumer actions such as clicks, scrolling behavior, zooming in on an image, zooming out, et cetera, everything is tracked. Finally, I observed the final purchase decisions and product returns, if any. So basically on the consumer side, I know what consumers see on the website, what they do on the website, and finally what they purchase or return. Finally, in the last part, in terms of the supply side, what I observe is the daily retail price and seller-set wholesale prices which allows me to calculate seller revenue and platform revenue and profit outcomes.

I hope the empirical setting is clear, and now I want to switch answering the research question. So the first question was about the impact of personalization, and by no means can I say something super generalizable here. This is a case study with Wayfair data, but the point I'm trying to make is to understand what is the impact of personalization in this particular case. So the way I estimate the causal impact of personalization using a large-scale field experiment. So together with Wayfair we took more than 9 million consumers. The experiment ran for two years. Consumers were evenly randomized into treatment and control group. So consumers in the treatment group would see personalized set of rankings. So same idea as before, the rankings are a function of consumers previous browsing history, versus in the control group, regardless of what consumers did on the website previously, they would always see bestseller, most popular product rankings. So this experiment allows me to compare the personalized set of rankings towards the business as usual bestseller rankings.

So what I find is the following. On the consumer side, consumers in the personalized group, they ended up scrolling less products. They filtered less and they purchased faster, meaning they economized two days when they were searching before purchasing. In general, they were more likely to purchase overall. So the first three sets of results, they're telling us that consumers are saving on the search costs in the personalized condition. The fact that they're purchasing more does not necessarily mean that they're better off. So to understand whether consumers are better or worse off, I look at the purchase outcomes.

What I find is that consumers in personalized group, they did end up purchasing slightly more expensive items, but at the same time they were 10% less likely to return the product post-purchase and they were also more likely to repeat purchase overall in the product category. I replicate these results on all product categories, but at the same time the main focus in the paper is on the dining chairs. One of the reasons the repeat purchase is important here is because consumers usually buy one or two chairs, they test them and then they buy the rest of the chairs set, right? In that sense, the repeat purchase is basically buying the same chairs just in a complete set. So the takeaway here is that on the consumer side, it seems that personalization can benefit consumers on average. Obviously, there is heterogeneity in the results in that personalization mostly helps consumers who have longer browsing history versus consumers who do not have browsing history, obviously they're not as impacted.

Now, on the supply side, what I observed is that on the platform side, the platform's revenue increases significantly by 2%. This is kind of mechanical because the purchase probability increased and also consumers were purchasing slightly more expensive items, so that's not surprising. What I saw was important to document in the paper is that the profit increase of the platform is solely driven by the fact that consumers repeat purchase. So it's not that consumers are purchasing higher margin items, which is exactly what the regulators would potentially be concerned about. Now, on the seller side, what I observe is that less experienced smaller sellers benefit the most from personalization with their revenue increases because they're now more visible on the platform. So personalization does not impact as much the large sellers, but it does impact the smaller sellers.

What I saw was also important is that usually when people talk about personalization, everyone remembers Chris Anderson's Long Tail literature where personalization should help consumers with niche preferences or very niche products. That's not what I observe empirically. Consumers who have very niche preferences, they usually do not benefit from personalization because they use very specific keywords because they know what they want and that's why they can find everything organically and very fast, versus personalization mostly benefits mid-niche sellers, so think about small local sustainable wood or stuff like that, this type of sellers. So the takeaway here is that given the Wayfair experiment, what I can say is that the personalization could help consumers. It can help platform and smaller sellers on the platform. Again, I do not claim generalizability in the sense that any platform might have a different setting, but at the same time, from the regulatory perspective, it's important to know that there will be different outcomes for different platforms, right?

Now the next question is how will privacy restrictions that limit consumer tracking impact this benefits? Just to remind you, the problem occurs because usually consumers arrive for multiple sessions, 40% are recognized through logins, 60% are only recognized through online tracking technologies. For example, one of the privacy regulations that is discussed right now is a Safari first-party cookie expiration policy where a Safari wants to set the first-party cookie expiration date to seven days. So what that means is that if the consumer arrives after more than seven days, their cookies will be deleted. So just to give you an example, imagine there is a consumer who arrives for three sessions. After the first session, it took the consumer more than seven days to arrive back and then she arrived within a week, for example, for the third session.

What the policy would do is the following. The platform would no longer be able to recognize the consumer on the second session because the session originated more than seven days after the first session, right? So basically the cookies were already deleted and that's why the platform has to work with the fragmented data instead of having a full consumer history. To give you a scale of the problem, on average, 30% of consumers arrive from Safari browser, which means it's like millions of consumers who will not be recognized.

To understand the impact of this type of policies, because a lot of those are in the future, what I do is the following. So I take the original personalization algorithms that the platform uses and then I retrain the algorithm using the lower quality of data. So remember that I know the source of traffic and the browsers that consumers use when they arrive on the platform. So basically I split the data manually as if consumers who arrive from Safari browsers after more than seven days of inactivity were not recognized, and I basically retrain the whole algorithm with lower quality data, and then that generates the counterfactual set of rankings that would have been generated under lower quality data.

Now, the next question is how will consumers respond to this counterfactual set of rankings? For that, I obviously need to simulate that and I developed a multi-session search model to understand that. The outcomes of interest in the model are the following. I'm interested how consumers choices will change as a result of counterfactual recommendations, what will be the outcome on the seller revenue and the platform revenue and profit. So in terms of the model, the model is as follows. So consumers arrive on Wayfair, they navigate to product ranking pages. They see only part of the page. So they have limited awareness and the reason is very simple because on your screen, you do not see all the products that are available. You have to scroll down to discover additional products.

Right away, in their awareness set, consumers observe the price rating and the image of the product. So those are observable product characteristics. They know their preferences towards this attributes. What consumers do not know is the product reviews and additional product details that they have to click on a product to reveal, and that's the origin of the search costs. Because some of the characteristics are observable and some are not, the true product utility is a priori unknown to the consumer. Following

Hodgson and Newey's paper, I assume that this utility is a function that is a draw from a Gaussian process. The reason I do that is because it nicely allows me to incorporate consumer learning in the search model.

Because consumers do not know the true product utility, they start forming expectations, right? So as a consumer I might think, "What is my expected utility from clicking on a product that I already observe on the page versus my clicking cost?" Or I could go down and discover additional products, so basically scroll down and discover additional products if my expected utility from doing that is sufficiently high, or I could leave the platform overall and just go to the outside option, or I could purchase the best products that I've observed so far. So these are the four actions that consumers are choosing from. Obviously, because the model example is complicated and it is really hard to solve in closed form, so I assume a near-optimal consumer solution where I assume that consumers are using upper confidence-bound algorithm when they search.

This is a very standard-bended algorithm where the idea is that consumers explore and exploit product space when they search on the website. At a high level, each consumer has an index about each product on the website, and that index is a function of the observable product characteristics and the uncertainty about the product utility. So if the index is sufficiently high, then consumers would click on a product, otherwise they can scroll down to discover additional products. Again, they could leave or they could purchase the best product as they've seen so far. Oops, sorry.

At the end, I write down the likelihood function of the observed search paths and I maximize it with respect to the data to feed the data the best, to estimate the consumer preferences and the underlying search costs. Because the model is complex, there are a lot of challenges with identification. First of all, there is indigeneity in the rankings where historical consumer choices affect how products are ranked and that affects how consumers choose in the future. Similarly, prices are endogenous, so historical consumer choices might affect how sellers set product prices, but at the same time that will affect future consumer choices. It's not very clear how to estimate the rest of the parameters.

To resolve those identification issues, I use the experiments, right? So basically the ranking experiment is creates this nice exogenous variation where observational equivalent consumers would see randomly different rankings and that creates exogeneity in the search costs and different product attribute preferences. Also, the bestseller algorithm that Wayfair uses is a Thompson sampling-based algorithm where it's the idea is that each product's rank is a draw from a posterior distribution. It's a random draw which creates this innate exogeneity in the bestseller rankings. The pricing coefficient is very hard to estimate without good variation. What I do, Wayfair ran a pricing experiment with a randomly changed prices for some consumers, and I use that experiment to create this IV for the price changes to estimate the pricing coefficient. Afterwards, in general, the nature of variation in the search patterns helps me estimate the rest of the parameters.

Just to remind you where we are, so I retrained the algorithm to generate the counterfactual rankings and then I will use this model to simulate how consumers would search in the future. One thing to mention is that it is very hard to trust the structural models, especially when they're too convoluted. So what I do is I validate the model using the actual Chrome policy. Basically, in 2020 in March, Chrome introduces blocking third-party cookies for a version of its browser for a month. The recognition rates for Wayfair dropped significantly in that particular version of the browser, which I use as a nice natural experiment variation to validate how well the model can predict the data in that. Due to time constraints, I'm not going to go too much. You can go to the paper to understand how well the model predicts out the sample.

Now, I want to talk about the impact of Safari policy. So what the model is predicting is that consumer welfare will decrease by almost 20% as a result of Safari restrictions. The main negative effect is coming for the consumers who are more price-responsive, versus consumers who are less price-responsive, they actually are not impacted as much and that came slightly as a surprise. But at the same time, when I look at the empirical historical data, it turns out that on average consumers who are more price-responsive, who are very responsive to sales tags, et cetera, they usually don't search as much, which means that if they do not find something relevant at the beginning, they just leave the website and they get an outside option utility of zero, versus consumers who are less price elastic, they would keep searching and that's why they would eventually find something relevant for them.

Now, on the seller side, what I observed is that smaller sellers revenue decreases by almost 6% as a result of Safari policy versus larger sellers actually are benefiting from these policies. This is something that I think should be underlined in all regulatory discussions in the sense that the marginal value of data for different types of sellers is very different. So for smaller sellers, the marginal value of a data point is very high because they don't have as much data and the algorithm would not pick them up and show them higher up on the rankings if they don't have sufficient amount of data, versus for larger sellers, even if they lose some part of their data, it's okay because they already have a lot of data for the algorithm to show them higher up on their ranking page results.

Now, on the platform side, what I also observed is that the platform's revenue decreases significantly as a result of Safari policy. At the same time, their profit does not decrease as much. So when I started investigating the cost data, it turned out that for the platforms, usually it is actually more beneficial to show larger seller rather than smaller sellers. The reason is that larger sellers, they have economies of scale. They can provide wholesale price discounts. They can provide cheaper shipping costs, et cetera, which is why the model is just predicting that a profit outcome will not be as impacted.

So the takeaway here is that unfortunately, the privacy regulation could hurt more price-responsive consumers and smaller sellers on the market. In this, if we start thinking how will maybe consumers are valuing privacy so much that this negative effect on the welfare will not be important to them. I do not have privacy valuation embedded in the model, so what I do is I kind of run a back of the envelope exercise where I estimate the privacy valuations outside of the model.

What I do is the following. So as I said, Chrome has this policy with a block third-party cookies. So what I do is I run the structural model on that period of time only to understand how much more prices paid or search costs paid were paid by the consumers in the version of the browsers that was affected compared to the version of the browsers that was not affected. Same thing for them. I redo the analysis looking at the consumers who were using Chrome version of that browser Chrome version 80 during this period, but then switched to some other browsers. Basically, I am trying to understand how much more do they overpay in terms of prices and in terms of search costs.

What I find is that no matter how I calculate on average consumer's privacy valuation bound is at $3.67 versus they would lose more in welfare after privacy regulation. So this 3.67 for consumer privacy valuation might seem a bit low because on average the literature is estimating five to $20 privacy valuations. But then if I look at the European data where the platforms usually are required to track who accepts cookies, who does not, what I see is the following. So I cannot show you the Y-axis, but in general the blue line here is a share of people who accept all cookies and it is very high. So on average, consumers, when they arrive on the platforms, they accept all cookies by default and they do not think much about the data that they give to the platform. So in that sense, the small privacy valuation estimate makes sense because consumers just simply do not think much when they give out the data. In the last part of the paper, what I start thinking about is what can platform do to mitigate the losses from privacy restrictions? So what I do is the following. I use the device level IP address and behavioral data on Wayfair to predict user labels even when the exact user label is not present for the platform. So it's an XGBoost-based algorithm. It's similar to random forest idea. Essentially, imagine there is a consumer who arrived from some IP address and they were looking for particular products on the website, then the next time someone else is arriving from the same IP address and they're looking for similar items, the chances are it's the same or very similar consumer, and then we can basically start showing personalization in a probabilistic way.

What I do next is I evaluate how would probabilistic recognition perform on the market using a structural model. Basically, the blue lines or the blue bars are still the previous Safari results that I showed you before and the green bars are the results from the probabilistic identity recognition. So what I find is that on average, all the results are going to be better under probabilistic recognition because now the platform does not know exactly who the consumer is, but they can probabilistically guess and still show personalized set of outcomes. So in terms of the key takeaways, what I learned from the project, and I hope I conveyed it here too, is that personalization is not necessarily bad. It can benefit consumers, sellers and the platform. Privacy regulation primarily is hurting smaller sellers and price-responsive consumers, and platforms can partially mitigate this losses if they use probabilistic identity recognition.

So in general, probabilistic identity recognition is sort of illegal in Europe because they don't want to profile people and there is a risk of profiling people incorrectly even when you use this type of algorithms, but I think it is one way to go where the platform still does not know who the consumer is, but they can probabilistically guess and still show personalized set of outcomes. Personally, I think it is way better than having consumers do biometric login because if you... I don't know if you've noticed, but some of the platforms, they actually introduce the biometric login option where you can log into the platform website using face or fingerprint ID, which I think is a different set of privacy violation versus this type of machine learning algorithms could help platforms operate under privacy regulation. Thank you so much. I really appreciate any feedback and thank you, Ginger, for discussing the paper. I'll click through the appendix.

Malika Korganbekova:

I will click through the appendix, sorry. Okay.

Ben:

And now as you may have guessed, we have Ginger Jin from the University of Maryland to discuss.

Ginger Jin:

Thank you, Ben. Thanks Pinar and other conference organizers for inviting me to discuss this interesting paper. I don't think I have any direct interest for or against Wayfair, but per Aviv's morning advice, when you're in doubt, you should disclose. And so I disclose that I provide consulting services to Amazon and Alibaba. And as far as I can tell, both marketplaces on Amazon and Alibaba has offered something, probably what we'll call furniture. I haven't checked whether they have exact, the same blue velvet dialing chairs. There are many antitrust experts in this room, so I will leave it to your judgment on whether this is relevant or not. But more relatedly, I'm very fortunate to have opportunity to work at FTC as the Director of BE about eight years ago. And that experience exposed me a lot to the privacy issues, to the data use issues. So I'm really glad young researchers like Malika has really picked up those issues seriously and writing such a fantastic paper.

I would like to encourage all of you, especially the students and young researchers in this room to really start thinking about the fascinating research area like this. So back to the paper, Malika already did a terrific job summarizing her findings, so I will be very brief here. You can see that she's addressing very important research questions, not only on whether privacy restriction would affect the platform, the consumers, and the sellers, but also how the platform and consumers are going to respond to that changes in privacy restriction. I think that equilibrium view is really, really important. And she has extremely rich data. It's not only who purchased what, but also to what extent they click to scroll, to tap, or hover, zoom, return and repeat customers. So this is really, really extremely rich data. She also have a lot of experimental variations, the randomized experiment that shut down the data available for personalization, but also the price experiment and many, many other experiments that allow her to really customize her model for the Wayfair data.

I really envy that kind of data access. And you can see that she has in-depth modeling and analysis, she has a very sophisticated model to capture consumer's search, purchase behavior. I want to emphasize that she actually allowed consumers to learn when the privacy restriction become imposed on the system. So I think that's a very important feature, a very laudable feature. And the platform's reaction, she has tried multiple ways, including adjusting the algorithm. So I really, really like that feature. So because the title of the paper is Balancing User Privacy and Personalization, so the first question I have in mind is, exactly what are we balancing against? It seems like the paper is suggesting personalization provide absolute benefits to consumers, to sellers, to the platform. There's some heterogeneity among different type of consumers and sellers, but it seems like, by and large, everybody benefit from it. So exactly what are we trading off against?

And we know that's Safari, Firefox, and Chrome's have all either implemented some restriction in privacy or plan to put those restrictions. And I would imagine that they do that because they think the consumers appreciate those privacy restrictions. Okay? And they impose this restriction on all websites, not just Wayfair or marketplace websites. So I'm sort of trying to think about exactly what the other counterpart we should think of in this balancing act. One idea is, maybe there are different types of websites, like some good websites like Wayfair, that people would benefit from personalization. But there are other websites, I don't know, phishing website, that the data collected from the users could be very hurtful to consumers. If that's a case, the policy implication could be very different from a blanket ban on personalization, right? Maybe we should allow consumers to have their own choice of which website they should allow the data personalization and which website should be blocked. And the findings that Wayfair is able to use probabilistic algorithm to somehow overcome the privacy restriction is kind of giving me a mixed feeling.

I feel like if Wayfair can do it, maybe some bad players can do it as well and probably even better. How we think about that for the policy perspective. Another trade-off I can think of is, maybe even within the same website, let's say it's a good website, the personalization actually could be used for multiple purposes, right? It's not just for the search ranking. I think Malika has shown very convincingly that the personalization could help the search ranking to be better presented to consumers. However, I can imagine that the same data may be used for price discrimination, may be used for different kind of targeting of coupons, right? Or maybe the shipping cost could be different, and maybe the inventory availability could be customized according to how much you have searched on Wayfair and how much you're willing to pay and so forth. So some of those might be not as universal as what you show here in terms of the benefits to consumers.

So maybe, could that be the trade-off, that somehow the personalization could be used for this universally good thing so-called search ranking? But it could generate a very mixed effects if you're using that for, say, price discrimination. So I don't know to what extent you can address this. And maybe that's another paper using similar data. The third one might be, even within the same usage, it could be is it possible that some users benefit from this but other users don't? And I don't have a good sense. Based on your results, it seems to show that everybody benefits from it to some extent. Okay. So this is probably more relevant for the motivation of this paper, and hopefully can encourage you to continue to work on similar topics in the next one. My second comment is, it seems like you estimate your consumer search model from two samples. So one sample is for those who come into the store from first-party cookies, and the second sample is for those who come in from the third-party cookies. Okay? They do those estimations separately.

However, in reality, I would imagine that the same customer could appear in both samples, right? Sometimes, I use the first-party to get in Wayfair, sometimes I look at Weather.com and the third-party cookie there track me and show me the ads of Wayfair for the blue chairs and I click into it, right. And this could have, I'm sort of trying to think what kind of implication this could have for your estimation. I can think of two. One is the selection effect. Those who use both first-party cookie and third-party cookie are maybe those who are eager to buy and less sensitive to price. And maybe that's kind of why you find different price sensitivity in your sample. Another could be the ripple effect in your counterfactuals. If you block the first-party cookie in one counterfactual, it may hurt the Wayfair's ability to use their third-party cookies on the same consumer. So I don't know whether there could be ripple effect in your estimation.

My third comment is about this probabilistic identity recognition counterfactual. That's kind of the counterfactual algorithms you think Wayfair could use to get around of the privacy restriction. I think the motivation on this could be better because I can see the motivation of the other counterfactuals very tied to Safari's policy or Chrome's policy, but this one seems like you've just kind of hypothetically assumed that you cannot track the same users across different devices. I'm not aware of any real policy that try to think of that somehow I allow you to be tracked, but I don't allow you to be tracked from an iPhone to a Samsung tablet, right? Maybe a better motivation on that would help readers to understand that. And some of the results seems to suggest that this algorithm that's not as good as the full level of tracking somehow can benefit some consumers. So maybe, could this be some of the trade-off that I was talking about? Maybe flesh out that a little bit would be good. Yeah.

Maybe this could be linked to other privacy restrictions, especially how this algorithm could address, say, Safari's limit on first-party cookie or Chrome's limit on third-party cookie. Those counterfactuals may be linked. And my last comment is, you have considered the platform and user response to the privacy restrictions. I would encourage you to think more of other potential responses. For example, I think the platform may change their pricing because of different privacy restriction. I know you're not focusing on the pricing at all, but I can't stop thinking about that. Maybe you could persuade me that I should not think more about that. But pricing seems to be quite important for the data use, at least intuitively to me. And consumers, you have incorporated their learning, which is really allottable. I would imagine that there could be other action changes, right? That you may change the way that you search on the website for example, and you may change the way that you view advertising if advertising become less targeted on other websites, right?

Maybe you're more willing to log in and become a member to Wayfair, for example. All these could change as a result of privacy restriction. And on the seller side, the seller side is really not touched by your model. You've sort of assumed the seller behavior, it's exogenous given. But I would imagine advertising may become much more attractive to sellers if the platform is not able to use individual data to provide personalized the ranking. Now the sellers have to compete against each other to get the eyeballs from the consumers. So maybe the platform could get a lot of advertising revenue out of that. So in that sense, the platform may not be worse off that much, but the sellers, especially those small sellers who have to struggle to get visibility could be much more worse off. So I have some technical comments we can discuss later on, but overall it's an amazing paper, it's an amazing job market paper. I really encourage every one of you to read the paper. It's really fascinating to see how much the industry-level data could be used for academic research. Thank you.

Speaker 23:

Now, we have time for some questions.

Malika Korganbekova:

I think there is a question here. There.

Speaker 24:

I'll start. On your right.

Malika Korganbekova:

Oh, there. Yeah.

Speaker 24:

This side first. Tremendous paper. It's so interesting to see the ways that privacy in practice personalization had such big benefits. And I'm wondering, probably not in this paper because it's such a complete paper, but could you do simulations to ask what if Wayfair were trying to use the data in a way to price discriminate or do some of the things that Ginger mentioned? In a sense, they have power via personalization, and here it seems they're using their power in a way that's aligned with consumers. What would be the worst case scenario? And could you do simulations to think about ways in which it could be used in less advantageous ways, what that scenario might look like and so forth?

Malika Korganbekova:

Right, that's a good point. I actually do have a paper now where we look at the different retailer pricing strategy in terms of different data when they use different data. So I didn't have a working paper, but it's something we're looking at because indeed to Ginger's point too, the advertising behavior, in general, is changing and the pricing behavior could also change. And this is something that I am exploring right now. Yeah, thank you.

Andrew Ching:

Okay. So yeah, thank you for your excellent presentations, and very interesting paper. So I am wondering, so you show that more personalizations lead to quicker purchase, right? And I wonder to what degree you can say, to what extent you can say this is actually a better match for the consumers. I can imagine if I am doing a search and the ranking of the products that show me is more or less the same a couple of times, then I may just say, okay, I'm just too tired, I just buy it. Right? But it's not necessarily giving a better match if I see more variety. I don't know, [inaudible 05:30:14]. Yeah.

Malika Korganbekova:

I think I see what you mean in the sense that maybe the platform could wear down the consumer in a way that they just want to buy and... So I think as a match value, as a quantifiable match value, I use the product return rates and repeat purchases because I don't know what the consumer's thought process is in terms of like how, when they decide what to finally purchase. I could potentially use the data to understand how similar the rankings were right before the purchase. Because if they were particularly similar and there was no diversity shown and that's why the consumer purchased, that could potentially be done because I do observe on each consumer page load what was shown at each session. Yeah. Thank you so much.

Speaker 23:

Any other questions? All right.

Malika Korganbekova:

Okay.

Speaker 23:

I think we can move on.

Malika Korganbekova:

Thank you so much. Thank you.

Ben:

And next we have Evan Starr from the University of Maryland presenting Clause and Effect: Theory and Field Experimental Evidence on Non-Compete Clauses.

Evan Starr:

Okay. Thank you so much to the organizers for having us here, and thanks to you all for sticking around. This is the last presentation before snacks. So I hope by the end of this you will say to yourself, I'm glad I stayed. Okay. And if not, then at least you'll get snacks. All right. So this is joint with Bo Cowgill, who's sitting here in the middle, and Brandon Freiburg from Columbia. And let me first disclose, this is a field experiment. We got some funding here from the Russell Sage Foundation, from the Smith Richardson Foundation, the Institute for Humane Studies, Columbia Center for Political Economy, and the Copper Foundation. And a full disclosure, I've also been retained as an expert witness in several labor market competition issues over the last few years. None of those have any interest in this particular paper. Okay. So first, I probably don't need to explain this to anybody in this room, but we should start with what a non-compete clause is.

It's a term in an employment contract that prohibits a worker from starting or joining a competitor firm within a particular timeframe after they leave, usually a year or two and within a geographic boundary. Okay. So here's a non-compete from Amazon where they're prohibiting a worker for 18 months after they leave from engaging in or supporting the development, manufacture, marketing, or sale of any product or service that competes or is intended to compete with any product or service sold, offered, or otherwise provided by Amazon. And so these are controversial restrictions. The folks in this room of course know that the FTC took a position on this in the last few years, and it's been a controversial position that has been playing out in the courts recently. And so I want to take for a moment the position of the case for non-competes.

Over the last few years, especially with the FTC comments that we've had, the case for non-competes has been made relatively clear. So what are the main tenets? The first argument that you often hear is that non-competes help firms keep proprietary innovations secret. Because they prohibit a worker from joining a competitor, they preclude that worker from sharing any secret information, and that thus maintains the firm's incentives to develop those secrets in the first place. Okay. The second claim that you often hear is that workers should not be worse off from signing an non-compete agreement since they can just decline to sign them or hold out for higher wages. Okay. Signing a non-compete agreement is voluntary and so workers wouldn't voluntarily hurt themselves. Okay? So what we're going to do in this paper is we're going to assess both of these claims theoretically and empirically. We're going to start with a simple model of optimal wage setting and non-competes. And the question we're going to ask ourselves is, how can workers be worse off under non-compete agreements? Okay. The crux of this paper though is a large field experiment where we worked with two firms in the finance industry. And what we did is, we worked with one firm and we made job offers to 14,000 individuals where we randomized the presence and salience and duration of the non-competes, and then we worked with a second company and then we hired folks from the first company. And we're going to test who joins the second company and who shares secret information that was shared with them. Okay.

So let me talk about prior research on these two claims and then I'll get into this study. So the first claim is that non-compete agreements help firms keep proprietary information secret. And again, the idea here is that a non-compete prevents a worker from moving, and thus prevents them from sharing. Okay. And so of course, there's many ways to protect information. We have NDAs where you can just directly prohibit a worker from sharing information. You've got a body of trade secret law. There's many other ways you can protect that information. And so whether non-competes are actually necessary to protect this information is sort of an empirical question. Okay. And so we have no direct evidence in the literature to date on whether non-competes actually deter secret sharing relative to NDAs. Okay? What we do have is, and this is really in part because we don't have any causal variation non-competes, but we also know it's difficult to measure knowledge flows because it's hard to measure whether secrets were actually shared across firm boundaries. Okay?

What we do have is mixed indirect evidence from various state policy shocks. So on a recent paper with Brad Greenwood and Bruce Kobayashi, we looked at whether non-compete bans increased trade secret litigation. And so if you ban non-competes, people are worried that workers are going to move more and they're going to share secrets, and then trade secret litigation is going to rise. And we didn't find that was the case. There's another study by Hiraiwa et al that finds firms don't value the ability to enforce their non-compete agreements. And then lastly, there's some studies on innovation and investment. And those broadly find that non-compete agreements or non-compete enforceability reduces innovation even if it spurs investment. This is all kind of indirect evidence. It doesn't get quite to the core of the issue as we see it. Okay. What about workers being better off under non-competes? Well, if you survey workers, you'll find that workers under non-compete agreements tend to have higher earnings than workers who don't have non-compete agreements.

And of course, the problem is multifold of this. One is that non-competes never come alone. They always come bundled with a whole set of other restrictive covenants, and non-compete use is of course not random. It's not random whether firms offer them and it's not random whether workers sign them. Okay. If you look at state policy shocks, there's a much bigger literature on this. And all of them basically find the same thing, that workers are worse off when non-competes are made more enforceable. Okay. The problem here is that these are better identified studies, but state policies are not the same as non-compete use. Even in California, for example, where non-competes have been unenforceable since the 1870s, non-competes are still used for workers there. Okay.

I don't know if John McAdams is here today, but John McAdams in his review of this literature now five years ago pointed out one of the core issues, which is still true today, which is that what we need here is further research that's going to establish the causal impacts of non-competes themselves, not necessarily the impact of state policies. Okay. A lot's happened since 2019, but we still have very little evidence on the causal impacts of non-competes. Okay. So let me tell you what we're going to do and what we're going to find. So in terms of our theory, it's actually going to be very straightforward. We're going to find that ex post harm from non-compete agreements arises from uncertainty about the enforcement of your non-compete and even the presence of your non-compete, which could arise if you didn't read your contract. Okay. And then there's various behavioral factors that could make that worse, such as present biasness and base rate neglect. Okay.

The field experiment looks like this. Okay. So in phase one what's going to happen is we're going to work with what we're going to call Firm A and we're going to randomize non-competes and wages in job offers to sent to 14,000 individuals, and then we're going to hire workers who take the jobs and then we're going to give them some secret information to do a task. Okay. After they're done, then we're going to wait a little bit and we're going to work with a second company. And that second company, who's a competitor, is going to try to hire the workers who were previously hired in phase one. And we're look at who joins the second company and then who shares the secrets. Okay.

In the third phase, we're going to have workers who are randomly in there, they're going to be in their non-competes for three to four months and then we're going to randomly start releasing them early. Okay? And then we're going to do a follow-up on them about a year later. Okay. So here's kind of the punchline results. What we're going to find is that non-competes reduce earnings and mobility, but they don't protect secrets any more than non-disclosure agreements. Okay. So this is going to be our punchline finding. We're going to find mechanisms that relate to a lack of contract reading and that a reminder of worker obligations is key for these results. Okay.One other kind of fun result that we didn't expect is that when you make a non-compete very salient to workers, that it selects workers who are more willing to break them. Okay. So if I put a non-compete in your face, the workers who are willing to sign that are less likely to abide by it. Okay. All right, so that's where we're going.

So let me talk about the theory here briefly. Okay. So we have a very simple model of contracting under uncertainty. We've got two players. There's a firm and a mass of workers. Okay. The workers are going to have some private distaste for the job, D. It's going to have some distribution, F. And the non-compete is going to reduce the net present value of future earnings by some amount, K, and there's going to be some... Then total distaste for the job is going to be D minus K, or we're just going to call that theta. Okay.

And the worker is basically going to figure out whether they're going to take this job with a non-compete, which is going to come with some wage, W, and then their private distaste, theta, or their outside option, which is normalized to zero. Okay. From the firm, the firm is going to get some value, V, from the worker. And if they offer a non-compete, we're going to say there's some value, eta, from the non-compete. And eta is going to be, we're going to assume it's going to be greater than K, greater than zero, and the firm is going to choose to maximize wages given their choice to use a non-compete or not. And so this is the firm's utility function here. The left term is the firm's marginal revenue, and then the right term is the labor supply function. Okay. The basic tension here is the same one that Gregor was highlighting earlier.

If you offer a higher wage, you cut into your marginal revenue per worker, but you're able to hire more revenue or hire more workers. Okay. So the sequence of offers here, so I don't know why the spacing changes, is that the firm is going to choose to use a non-compete or not. They're going to set an offer, an optimal wage workers sign or not, and then outcomes are realized. Okay, I'm just going to summarize the findings for you here. So the baseline result is that non-compete agreements can benefit both firms and workers, and this is a standard result. Effectively what happens is, if non-competes benefit the firm by eta, the firm can take some of that eta and compensate workers for their cost of K, and everybody's better off. Okay. And this is sort of the baseline result that underlies, I think, the critique of maybe why non-competes can be good.

So how can you break this? All right. So the first thing we're going to do is add uncertainty about non-compete enforcement. Okay. So if you allow workers to have different beliefs about whether they think the firm is going to go after them with regards to the non-compete, then the workers who sign the non-compete are going to be the one who think it's not enforceable. Okay? And this is going to reduce the compensating differential that's associated with non-competes, and the workers who are harmed here are the workers who are then wrong about enforcement when they assumed it wasn't going to be enforced and then it actually is. Okay. The other thing you can do is you can add uncertainty about the presence of a non-compete agreement. All right. So if workers don't even read their contract altogether, then there's no compensating differential for the non-compete, and then workers who have unknowingly signed a non-compete become worse off later because they suffer this penalty, K. Okay. And then behavioral factors are going to make all of this worse.

Okay. So that's the model. So let me turn to the experiment, which is really the bulk of all of this. The population that we're studying is contract HR recruiters. Okay. And so let me break out why we're studying this population very briefly. Let me talk about the contract part work, worker part first. Okay. So contract workers are sort of interesting because they should be especially unwilling to give up their freedom to work because their ability to make a living depends on their ability to work with multiple employers. Okay. But they mostly don't interact with each other, which makes SUTVA violations a little bit less likely. Okay. They're of independent business and policy interest. If you go to LegalZoom, you'll see articles like how to use a non-compete when you work with independent contractors. In terms of policy, here's the... The New York City Council proposed a law to ban non-competes for freelancers.

They say, covenants not to compete are increasingly common in contracts between hiring parties and freelance workers. And they have a bill that would prohibit non-competes for those workers. Okay. What about HR? Why are HR workers important? Well, HR recruiters are a growing part of the U.S. labor force. They have access to very valuable information because they know who works where, they know who's potentially mobile. They sign non-competes at a relatively common rate, slightly more than average, about 20 to 30%. Maybe most importantly though, they're aware of non-competes and the harm they can cause because they're engaged in hiring workers. Okay? They're also may be experienced in bargaining. All right. And so, what do we think here? We think that by setting this population in any field experiment, you're limited in terms of generalizability. Here we think that, we think contract HR recruiters should probably be more averse to non-competes are and less likely to be harmed by them than at least the typical worker.

Okay. Let me tell you about the sampling frame here. What we did is, we worked with Firm A to identify about 30,000 HR recruiters on a platform. We took a stratified random sample of those 30,000, and then we're going to inverse probability weight our sample to reflect our 30K population. And here's what our sample looks like. They have an asking rate of about 50 bucks an hour. Most of them have experiences in recruitment and finance. The one thing I'll highlight is that we do a variation in the states where these workers live. And so the bottom row there, 70% of workers live in states where their non-competes are potentially enforceable, but in for 30% of the workers, their non-competes would be entirely unenforceable in their states. Okay. So we'll exploit that later. Okay, here's the experimental manipulations. So when it comes to the non-compete, the control group is we have no non-compete. Workers have an eight-page employment contractor and the signature is required at the end.

Our first manipulation is that we include what we're calling a hidden non-compete. We're using the word hidden here because we're going to contrast that with a salient non-compete. You should think of this as the normal condition. Okay. This is a normal non-compete. It's identical to the no non-compete, except until you get to page seven where there's a small little paragraph that includes the non-compete. Okay. And then we have the salient non-compete, and the salient non-compete is mentioned in the job offer. It's right up front, it's on the very first page of the contract, and it requires a separate signature. Okay. So you can't miss it. Okay. All contracts also had a non-disclosure agreement. They used Florida law where these firms had offices. And all signatures were checked. Important details because we are the ones working with these individuals, we were able to record how many milliseconds they spent on every page of the contract. And importantly, there was an option at the bottom of the contract to click go to the end and sign. And if you did that before you hit page seven in the hidden condition, then you wouldn't know that you have a non-compete agreement. Okay. So here's what the non-compete agreement looks like. This is the salient page one. It says, during the paid engagement with the company and for a period of six months after, the recipient will not directly or indirectly engage in any business that competes with the company, including but not limited to, business engaged in finance, technology, healthcare, publishing, philanthropy, or sustainability. The geographic areas is the United States. Okay. So it's a relatively broad six month that covers where the firm has financial investments. You'll notice that signature on the bottom page. Okay. If you're in the no non-compete or the hidden condition, this is your first page here. Okay.

It's called a non-disclosure and work agreement. And you'll see at the bottom, there's that button to go to the end and sign. All right. So what we're interested in here are two parameters that you can think about. The first one is taking the perspective of the firm. If you're a firm and you want to ask the question, what's the causal effect of requiring a non-compete agreement in my job? Okay. That's basically what we did with our manipulations. And so it's a very simple, straightforward test. We're just going to compare the salient to the hidden to the control condition. And so we're going to estimate models of this form. We're going to include strata fixed effects based on how we sampled our individuals. And then we couldn't invite 14,000 people on the same day, so we're going to include fixed effects for the time in which they were invited.

Okay. The next parameter you might care about is, if you're a worker, what's the effect of signing this non-compete agreement? Okay. Now, this is actually harder to estimate because of course workers choose to sign a non-compete, right? And so it's actually very hard to get somebody to randomly sign something. Okay. So how are you going to disentangle this selection and treatment here? All right. So the first thing we're going to do is, we're going to estimate a local average treatment effect for the skippers. These are the people who skipped page seven of the employment contract and the hidden condition and the control condition. And then later they're going to get a reminder about their non-compete, and that's going to change things. Okay. We're going to instrument for whether people have accepted with an invite date. It turns out, here's the instrument. It turns out if I sent you a job offer randomly on a Friday, you're much more likely to take it than If I give that offer to you on Saturday or on Thursday. Okay. So just the day that you were sent the invite shifts around the job acceptance rate. Okay.

And then the last thing we're going to do is, we're going to take the workers who have selected it into non-competes and where they're going to randomly let them out of non-competes. Okay. And that's the other way to address this challenge. Okay. So let me tell you about phase one here. So in phase one, here's the detailed overview. Firm A is going to send out these job offers. They're going to randomize the non-compete treatments. They're also going to cross randomize wages between $25 and $60 an hour. And then we're going to test who read the work agreement, who signed it, when they signed it. They're doing an HR task for the company, which is they're going to review resumes that was sent for a recent opening. Okay. This is the secret information that they're going to get. They get sent resumes that they're supposed to review for the company. They're real resumes, although we did change the names to make the names anonymous. Okay.

Then they submit the resume and then they're done with Firm A. Okay. So let me just show you a bunch of results in bar charts. Okay. So here is the opening, the contract rate. I'll show you all the bar charts have the same flavor. On the far left is the control group, on the far right is the hidden, and the middle is the salient, which I blocked out here. And so you can see that about 20% or 22% or so open the non-compete, open the contract. In terms of signing the contract, we dropped down to about 15% and 14%. And then when it comes to finishing the task, we're down to about 12% and 11%, and we can't reject that those are different from each other. Okay.

When it comes to this, we can say this is about 8% drop. And actually because we randomized wages, I can tell you this is equivalent to about a $6 an hour difference. Okay,. In the salient group, the salient group, about 15% of them opened the contract, 13% of them signed it, and 10.2% of them completed the task. And we can reject that difference from the no non-compete-

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We did the task and we can reject that difference from the no non-compete group. That corresponds about a 15% drop in task completion rates, and that's the equivalent of about $13 an hour in terms of the initial job offer. You might want to know who's driving this. We have a lot of heterogeneity in the paper. I don't have time to get into it, but I'll tell you what's driving this first stage result is, it's women are the ones who are more sensitive to a salient non-compete. It turns out men sign at basically, similar rates regardless of what's put in front of them. And people who have high asking rates are also deterred.

All right. What about reading the contract? So here's the distribution of the number of seconds spent on the non-compete page, conditional on opening the contract and getting to that page. So the salient group is in the gray bars, and you can see that there's a huge mass at 60, which means that most people spend over a minute on the first page of the contract. And contrast, the hidden group, there's a huge mass on the left, and the people who spent zero seconds are what we call the skippers. And you can see these are about a third of the hidden. They skipped the non-compete altogether. On average, about 75% of workers spend less than 10 seconds on the hidden page seven. Okay?

You might want to know how reading relates to whether you actually signed the contract. So what I'm going to do here is just look at how many seconds they spent on page seven of the contract. Remember the no non-compete and the hidden non-compete are exactly the same up until this point. And so you'll notice here in this bin scatterplot that they followed the exact same trajectory in terms of signing the contract until you get about six seconds in. And then the people who read the non-compete caught that about six seconds, their likelihood of signing the non-compete drops off by about 15 percentage points. So hidden readers are less likely to sign the non-compete agreement. It's just that in fact, most people don't really get that far.

Okay. All right. What about bargaining? So we captured attempts to bargain via messages. 1.1% of workers did try to bargain. Our protocol is to offer no raises. So you can think of this as like a wage posting model. So what we find is that recruiters do bargain. They tend to bargain over wages though. On the left here, I'm showing you this is the probability that they bargained if you were offered $25 an hour, and you can see here there's really no difference across the non-compete conditions between 1.5% and 2%. If you're offered 60 bucks an hour, you're much less likely to negotiate. And so we can't reject any differences across these patterns.

What about compensating differentials? So what we're going to look at here is whether workers who sign the non-compete agreements are paid more. What we would expect is that if I offered you 60 bucks, you'd be more likely to accept the job if a non-compete came with it than if you had a non-compete and a $25 an hour job. We don't find any evidence this is the case. In fact, what's happening in the data is that workers, regardless of what I pay you, are similarly likely to turn down the job whether you're offered $25 an hour or $60 an hour. And the result is that when you look at who takes the job, they all get paid about the exact same thing. It's about $45 an hour. That's their average hourly wage, but they can vary in how many hours they work. And so we see the same thing that we can't reject any differences.

So the punchline here is that the cost of the non-compete, at least in this context, is not in actually paying workers higher wages. It's that it reduces acceptance rates. So it's harder to find workers who are going to necessarily agree to your job. All right. Phase 2. So Phase 2, the way Phase 2 works out is that firm B is going to come in here as a competitor to firm A. After the engagement with firm A ends, they're going to make offers to every worker that was hired by firm A, and they're going to randomize the wages between $27 and $62 an hour. The task for firm B is that firm B is a similar finance company, and what they need is they're sourcing leads for an opening. So they're trying to find leads. Everybody who is in this experiment could give them leads. All they have to do is share the resumes that firm a shared with them. So this is going to be our measure of secret sharing.

So what we're going to look at is whether workers accept or not firm B's offer. We're going to see if they share resumes. And then part way through this engagement, firm A is going to send a reminder message of what workers agreed to. Think of this as like a standard exit interview where you get sit in front of HR and they say, "Hey, here's your contract, here's what you agreed to." And then firm B tasks are going to continue and ask for more leads. And then the firm B engagement is going to end.

Okay, let me preview that the reminder is going to do a lot of work here. So I want to read part of the reminder too so you can see what they were sent. And the highlighted part here is the part that was sent to those who had non-compete. Okay, it says, "Dear name, as part of our work together, you agreed both to a non-compete clause as well as to non-disclosure restrictions. This is a reminder of those obligations." We then defined it from their contract and said, "Please note, we take your continuing compliance with the non-disclosure and confidential obligations seriously, and we expect you to comply."

So let me just tell you the reactions to the reminder here very briefly. Well, I should say most of the reactions were of the form, thank you for letting me know. Of course, no problem. I signed up. But there were a few people who were upset, and then some people declined that they weren't going to work with the second company anymore because they were scared they would reveal something. So this goes even in the control group, people are deterred.

So what we did is we threw their responses into DistilBERT to look at the sentiment of their responses. And so the likelihood that you had a positive sentiment in your response was much higher in the control group than it was if you had a non-compete agreement, and the likelihood you had it had a negative sentiment was much higher if you're in a non-compete group versus the no non-compete group. So I'm previewing what's going to happen here. All right, so here's what happens after the reminder.

In the control group, we've got 36% of workers joining firm B. We have 28% in the salient group, and we've got 17% in the hidden group. So when I say the group, the workers with hidden non-competes are more likely to join firm B. It's this pattern that the salient group is more likely than the hidden group to join. And we expected that because we think they're selected on beliefs that the non-compete probably is not going to be enforced against them.

Now there's a question about what happens before the reminder. Here's what happens before the reminder, and I can sign these dollar values here. I can tell you that the hidden non-compete costs $43. That's the equivalent of $43, and 21 for the salient. Pre-reminder, we see nothing. Pre-reminder, we find no differences. The non-compete does not matter whatsoever, including for the people who had the non-compete right in front of their faces. So when I say reminders are key, this is what I'm talking about. Okay, what about the skippers? So the skippers should be identical. So we're going to take the skippers in the hidden group and compare them to the skippers in the control group, and they should be identical until the reminder, because the skippers don't know about the non-compete until they get hit with a reminder, and that's the first time they learn what was in it.

So when we look at the pre-reminder, we find that they join at basically the same rates, and then you can see after the reminder they're far less likely to join company B. What about when non-competes are enforceable versus unenforceable? Let me just split out our post-reminder results by the actual enforceability of the non-compete. So if you're in a state that could possibly enforce your non-compete, this is the pattern we observe. It's the same as before.

Now on the left I'm going to show you the same graph, but these are workers in states where their non-compete would not hold up in court at all. And here's what we find. You can see it's exactly the same. All right, what about sharing firm secrets? So overall, before the reminder happens, we find about 4% of workers share secrets. We can't reject any differences with non-competes. They share at similar rates. After the reminder, we find the same thing is true. After the reminder, people share less. But even though the non-competes dissuaded mobility, it didn't add any extra protection in terms of protecting secrets.

So Phase 3. Phase 3, what we did is we are going to randomly release workers early from their non-compete and give them another chance for follow-up work. So let me just show you the result here. So what's happening in this case is everyone's getting sent a job ad and given the opportunity to apply, but some of them have not yet been released from their non-compete agreement and others of them have.

So on the left here, I'm going to look at these are workers who don't have a non-compete, and some of them have gotten... So everybody gets a reminder here, and the people who don't have a non-compete get reminded about their NDA. People with a non-compete get reminded about their NDA and released from their non-compete. So if you have no non-compete, it doesn't matter whether we send you a message, a reminder at this point. If you do have a non-compete but you haven't been released yet, we find you're far less likely to apply for this job. But once you've been released from the job, you partially respond and move upward. So this suggests that again, the non-compete was holding workers back from taking this over job.

Lastly, what we did is we waited a year. It's very painful, but we did. We waited a year, and then we scraped their earnings on this platform. And we were curious, how does the non-compete agreement... If I randomly offered you a non-compete agreement versus the same job with no non-compete, or even no job at all, how does that affect your earnings? And the punchline finding here is that if I offer you a job with a non-compete agreement, we find that it reduces your earnings by about 4.5%. This effect is driven almost entirely by the hidden group. They have an effect size that's about twice as big as the salient group, and for salient, we can't reject a zero here. Let me just jump to the last column here. For the skippers, these are the people who skipped page seven, they drive an enormous part of this earnings loss. We find that they have earnings losses about 21% if you skip the non-compete entirely. Again, this is on the platform.

So let me talk about generalizability, and then I'll wrap up here. So what do we think we might generalize to? So HR contractors we think are probably more sensitive to non-competes than the average worker. What we think here is we've studied secret sharing, but only with regards to things like client lists. Trade secrets might be different here. The results are also specific to the contract terms used. You could replicate this experiment, but maybe with a narrower non-compete or a broader non-compete, you might get different results. Per IRB, we couldn't actually enforce the non-competes and file a lawsuit and serve people with papers. And so you might imagine if you could do that, you would also get different results. We do think this lack of reading seems like a general problem. Let me give you some evidence of that.

In a prior survey, we asked workers... This is a national representative survey. They told us they had a non-compete. We asked them how carefully did you read your non-compete? Did you read it? Not at all. Did you read it a lot? Did you consult? And this is the probability that they read the non-compete quickly or not at all. And you can see that HR falls within office support and business finance, and between about 40% of those workers said they read it not at all or very quickly. And that's conditional on knowing they had one.

We do a whole bunch of robustness checks in the paper about contamination bias, multiple hypothesis testing, randomization inference, weights. The limitations that are key is we can't measure performance off of the platform. Sorry, we can't measure earnings off the platform. So that's a real limitation. And so let me just conclude with I think our contributions here. We find that non-compete agreements reduce earnings and mobility without adding protection for secrets. Lack of reading and reminders are our key mechanisms. It's really not hard in our context to get workers under a hidden non-compete, but it's very hard to get them out. We find non-competes matter, even when they're unenforceable, and they may add little value to companies actually from secret protection perspective.

Again, this may be a counterintuitive result that if you make non-compete super salient that it selects workers who are unlikely to abide by them. And we think that our theory about the uncertainty and contracting uncertainty that implies ex post harm. We think this is a broader issue, and might relate to other contract terms like NDAs, non-solicits, liquidated damages for instance, et cetera, et cetera. So thank you so much for the time and to Ananya for discussing our paper.

Speaker 25:

And as your penultimate treat before snacks, Ananya Sen from Carnegie Mellon to discuss.

Yanyou Chen:

So thank you so much for having me. One second. Let me just see if this [inaudible 06:03:22] slides. Okay. Yes. Okay, cool. Okay, so thank you for having me to discuss this really cool paper. I'm the fourth person who's talking about non-competes today. Gregor, Heski, Evan and me. So I'll overview. If you haven't followed till now, maybe you're a lost cause. And if you have been interested, then maybe I don't need to go into the details. But non-competes prevent people from joining a competitor firm. There are concerns about mobility and how it might impact earnings, but workers could get compensated if they bargain enough to balance it out. What's the upside from the point of view of the firm? They might prevent sharing of proprietary information. Of course, if enforceable, the longer-term outcomes would be that they could limit entrepreneurship and innovation. Just as a caveat, a bit like Heskey, I don't work on non-competes, but I'm bringing an online platforms and field experiment perspective here.

So I've learned a lot over the past couple of weeks, and it sort of makes my head spin. There have been changes over the past decade across states, across industries, even within industry in terms of worker types. So this is, as everyone's mentioned, that it's a super important issue. Very quickly, the experimental design is that the authors collaborate with firm A, They randomize the salience of the non-compete clause, as well as cross-randomizing wages. And then they see who opens the contract, who signs, who completes the task. And then in the second stage they collaborate with another company, and try to see whether people will break their non-compete. Finally, they also have a release and follow up. They look at earnings down the road.

So if non-competes are salient, then people are 34% less likely to open the contract itself. I'm going to comment on this point in terms of identification a little bit. They're 15% less likely to accept jobs. Post-employment reminders make people realize that they haven't read, and deters them from joining competitors. So this is very credible. But they don't necessarily share client lists. Workers with non-competes have lower earnings down the road. So Evan was very clear. I think that just in terms of my first reactions to the paper, this is a great paper. I said that I work on platform stuff. I run field experiments. I also give a ninety-minute talk to first-year PhD students about how to collaborate with companies. And here they're first collaborating with company A. Then they're collaborating with a competitor company, and then they're following up after a year. They're also collaborating in the context which is not standard. This is non-compete.

As someone who runs field experiments, I was so excited to see this being implemented. So really hats off just in terms of executing this. Also, I think important insights. As Evan mentioned, a lot of the literature focuses on natural experiments that are created by state laws, and this was a really cool way of leveraging digital footprints to highlight the fact that people don't read that much and people might not be aware. And that I think really adds to the conversation.

Also overall, I buy the findings. For example, the reminder intervention, which prevents job mobility, I think it works on exactly the workers you think it should work on. So overall convincing, well-written. I've gone through two, two and a half versions of this paper, and so I encourage all of you to read it. But of course as a discussant, I'm trying to get the authors to tie up the loose ends. So just in terms of the context, as a reminder, the context is a one-off, one-hour job on the platform. So when we see minimal wage bargaining and explicit sharing of client lists, how much can we extrapolate? So this is a downside of field experiments in general, but I think a deeper conversation around this could be helpful. Of course, when companies' names are anonymized, it allows you to partner with them, but then there's a gap in extrapolation to other contexts that we might care about.

Another thing would be to actually leverage some of the heterogeneity, maybe by experience to shed light on the role of beliefs and information that might be driving the results. I know that you've done some survey stuff, which I really liked. So now that the experiment is over, another wave could be to just survey people to understand what their beliefs and information is, including what they might be doing off platform. Now that might lead to your corpus of text, including a lot more curse words, but might be worth a try to just do it descriptively.

In terms of identification, I've spoken with the authors about this. Some of the selection stuff is interesting just as an outcome, but at each stage there is a change in the composition of people who are proceeding to the next stage. I was thinking about this when Andrey was presenting stuff about his [inaudible 06:10:32] versus [inaudible 06:10:32] and how things are changing at each stage. So it might be useful to demonstrate what sort of selection effects are we seeing at each stage, and are we maintaining the balance on observables that we started out with right at the beginning. And the intervention starts with the initial email itself where the salient non-compete is made extremely salient. Of course, the second point about the identification is that these are people on a platform. It reminds me of gig work. But from stuff that I know of other projects out there, a lot of these gig workers and people who are on survey platforms, et cetera, they have their own Reddit groups. So it's just as an FYI that you might be violating SUTVA through that, but hopefully it's not that big problem.

Final thought, as I said, I was extremely excited to see this experiment being implemented, and we all love to randomize, so of course it's really cool. But then I also took a step back and I was like, "I've just started teaching a course on A/B testing at CMU, where I spend a lot of time talking about the ethics of experimentation." So the fact that okay, firm A and firm B know that they're in on it, but the workers don't. I'm really glad that the IRB approval went really well. But I think maybe a conversation in the paper about the costs and benefits of this would be extremely useful. If nothing else, I'll use it to negotiate with the CMU IRB next time I have a project with them. These are just some examples that I teach in class about different experiments that tech companies run. But overall, it's a great paper and I encourage everyone to read it. Thank you so much.

Speaker 26:

All right. And we have time for a few questions.

Speaker 27:

Thanks. This is just a super cool paper. One suggestion I had, if you haven't done it in the paper itself, is to look at your standard errors and try to talk about how precise your nulls are. What effect sizes can you rule out? I think that could help understand exactly how to interpret some of the null results here.

Evan Starr:

Yeah, that's a great point. Yeah, we could work on that for sure.

Speaker 28:

Could you say more about whether these non-competes are usually used in this industry, and how that compares to others? Would people be expecting that this would be in their contract or not?

Evan Starr:

So I mean the finance industry actually is really... The finance industry in New York blocked a non-compete ban from coming in the state of New York, which was passed by the legislature, and then they lobbied the governor to keep non-competes. I mean, our sense is that non-competes are actually quite common in the finance industry. And with HR recruiters, the companies that we're working with have used them with HR recruiters in the past. So this is something that's happening. It's happened with freelancers, it happens with hairstylists who are independent contractors, it happens with yoga instructors. All sorts of independent contractors have these sorts of agreements. It's relatively common in our context. I mean, at least in line with national estimates.

Speaker 8:

Hey, so different US states take often widely differing approaches to non-competes. They have different levels of restrictions and so on. California for example, bans them completely, and you have Silicon Valley over there. But then I wonder, you also have states like Wisconsin, for example, that have a smaller but still thriving tech sector where non-competes exist. I think Massachusetts too. To what extent, I wonder is that differentiation possibly a good thing in terms of providing a market for companies to go and set up and create jobs otherwise wouldn't be there because they really want non-competes that badly?

Evan Starr:

That's a great question. Part of a bigger discussion about the role of federalism and navigating cross-state issues. I'll just mention, of course, variation is great for empirical purposes so we can learn, and probably for companies and workers so they consort. But one of the lessons from the history of California at least, is that firms were getting around California's ban on non-competes for many years by using choice of law and choice of form clauses where they would stipulate another state's law in their contract, and that's how they were getting out of the California laws, until effectively, in 2017 or so, California passed a law that said, if you're in California, we're going to give you California protections. So there's ways to get around state-specific restrictions in this way.

Speaker 26:

Any other questions? All right.

Evan Starr:

All right. Thank you everybody.

Speaker 26:

We'll wrap it up.

Sam Kleiner:

Okay, everyone just wanted to thank everybody for coming. That concludes the day's events. Please join us tomorrow at 9 A.M. for the remainder of the conference. Also, there's going to be a reception outside with food, and I wanted to also just thank the Tobin Center at Yale for providing all the food. Hope to see you both outside right now and tomorrow morning.