Work Intensity in Equilibrium*

Jonathan V. Hall
Uber Technologies

John J. Horton
NYU Stern

Daniel T. Knoepfle
Uber Technologies

January 26, 2018

Abstract

In the ride-sharing markets created by Uber, demand shocks created by sudden Uber-initiated fare changes are primarily met by large changes in driver *physical* productivity. When fares are increased, passengers request fewer rides and drivers are less busy; when fares are decreased, passengers request more rides and drivers are busier. We find that the driver hourly earnings rate—essentially the market equilibrium wage—moves immediately in the same direction as a fare change, but that these effects are short-lived, as changes in driver labor supply on the intensive margin counteract changes. The prevailing wage returns to its pre-change level within about 8 weeks. Our results imply that the driver supply of labor to ride-sharing markets is highly elastic, most likely because drivers face no quantity restrictions on how many hours to supply. Our key finding is that work intensity is not a fixed attribute in these markets but rather is determined endogenously, in equilibrium. This endogenous work intensity perspective is central to understanding market equilibrium.

JEL J01, J24, J3

*Thanks to Andrey Fradkin, Steve Levitt, Keith Chen, Judith Chevalier, Mark Duggan, John List, Ed Glaeser, Austan Goolsbee, Robin Yerkes Horton, Peter Cohen, and especially Jason Dowlatabadi for assistance, helpful comments and suggestions. This manuscript was not subject to prior review by any party, as per the research contract signed at the outset of this project. The views expressed here are solely those of the authors.

1 Introduction

Employers expect workers in a job to have some level of productivity, which workers can meet, in part, through their choice of work intensity. Although expected work intensity might seem like any other disamenity requiring a compensating differential, it requires a different economic analysis. First, because work intensity affects productivity, it should be reflected directly in wages: a firm expecting workers to endure 20% greater work intensity has to pay *at least* 20% higher wages, whereas a firm expecting workers to endure 20% dirtier working conditions has to pay the (unknown) cost of that dirtiness to the marginal worker. Second, work intensity affects total output and hence the resulting equilibrium quantities: if all firms in an industry expect workers to work $x\%$ more intensely, then the same level of product market demand can be met with $\sim x\%$ fewer workers. Having implications for both market prices and quanities, work intensity is potentially important, and yet its role is not typically even modeled, with workers just assumed to have fixed productivity.

In this paper, we explore the role of work intensity in a market equilibrium, using data from a collection of Uber-created ride-sharing marketplaces in the US. Because of the computer-mediated nature of our setting, work intensity is measured essentially without error, as are hours-worked and product market output. Our main tool for studying work intensity is a collection of city-specific changes to the fare faced by passengers, which in turn affect demand and, at least in the short-run, the hourly earnings rate of drivers.

The market adjustments we observe in response to price changes are wholly inexplicable without appreciating the role played by work intensity in market clearing.

The fare changes that we use are changes to the "base fare," or the per-distance and per-duration rates that are used to calculate the cost of a trip under "normal," non-surge conditions. These fare changes create short-run changes in both the demand for rides and the per-trip payment of drivers. By observing the subsequent adjustments to bring the markets back to equilibrium, we gain insight into how these markets clear. Our research question is the role work intensity plays in this adjustment process.

In this paper, we report results from a collection of marketplaces in which work intensity is precisely measured at the individual level. Our setting is 43 city-specific ride-sharing marketplaces created by Uber in the US. The scope of our data allow whole markets to be our unit of analysis. For work intensity, we measure the fraction of an hour-worked that is spent transporting passengers. Because of the computer-mediated context, this work intensity is measured essentially without error. Matching our equilibrium conception of work intensity,drivers have only very indirect control over how busy they are, as Uber matches passengers to riders.

While the personnel economics literature is almost singularly focused on increasing worker productivity

In the personnel economics literature, this choice is typically presented as being made in response to the incentives faced created by their firm (Lazear, 2000; Akerlof, 1984; Bandiera et al., 2010; Mas and Moretti, 2009).

When workers with fixed hours say they are "busy" at work they do not typically mean their employer recently increased their piece rate and they are responding accordingly—but rather that they have more work to do because their firm is more business.

Although workers are commonly modeled as having a fixed technical productivity, it is clear, empirically, that productivity can vary not only between workers, but also within workers, over time. In the personnel economics literature, this within-worker variation—how hard a worker chooses to work—is typically presented as an individual choice made in response to the incentives faced created by their firm (Lazear, 2000; Akerlof, 1984; Bandiera et al., 2010; Mas and Moretti, 2009). Although any observed work intensity is a choice—workers can always quit—casual observation suggests that much of the variation in work intensity is in fact "demand-driven": when workers with fixed hours say they are "busy" at work they do not typically mean their employer recently increased their piece rate and they are responding accordingly—but rather that they have more work to do because of the ebb and flow of demand and their firm's current level of staffing.

Although a worker is perhaps unlikely cite market-level explanations, to the extent demand shocks occur at the level of the market, then a worker's busyness depends not just on their own firm and co-workers, but also on the collective staffing decisions of the firm's competitors. If greater work intensity is a disamenity, the individual choice of whether to accept a certain wage with some known level of required work intensity in turn affects—and is affected—by all other similarly situated workers. We would expect work intensity to be reflected in equilibrium wages. This characterization of work intensity suggests the usefulness of an equilibrium view of work intensity. The idea of equilibrium busyness is similar in spirit to the equilibrium treatment of hours-worked and the firm preferences for workers versus hours (Rosen, 1968). However, this framing of equilibrium work intensity—despite being potentially practically important—faces the empirical problem that work intensity across whole markets is not typically measured, unlike say wages, number employed, and hours-worked.

In this paper, we report results from a collection of marketplaces in which work intensity is precisely measured at the individual level. Our setting is 43 city-specific ride-sharing marketplaces created by Uber in the US. The scope of our data allow whole markets to be our unit of analysis. For work intensity, we measure the fraction of an hour-worked that is spent transporting passengers. Because of the computer-mediated context, this work intensit is measured ssentially without error. Matching our equilibrium conception of work intensity,drivers have only very indirect control over how busy they are, as Uber matches passengers to riders.

Our main tool for studying the collection of marketplaces is a collection of city-specific plausibly exogenous changes to the fare faced by passengers. We explore the effects of Uber-initiated, city-specific changes in the fares faced by passengers. The fare changes that we use are changes to the "base fare," or the per-distance and per-duration rates that are used to calculate the cost of a trip under "normal," non-surge conditions. These fare changes create short-run changes in both the demand for rides and the per-trip payment of drivers. By observing the subsequent adjustments to bring the markets back to equilibrium, we gain insight into how these markets clear. Our research question is the role work intensity plays in this adjustment process.

When Uber lowers the fare, passengers want to take more or longer rides, while drivers want to supply fewer, as drivers are paid a fraction of the fare collected from passengers. This creates a imbalance of supply and demand that must be resolved as the market moves to some new equilibrium. Movement towards a new equilibrium could happen though a number of non-mutually exclusive channels. One, dynamic or "surge" pricing could essentially "undo" all or part of the fare change. Two, service quality—particularly wait-times—could change, shifting the demand curve and counteracting the movement along the curve, though surge pricing is intended to limit this margin of adjustment. Three, driver work intensity, or technical productivity, could change, with the same active drivers providing more or fewer rides during an hour of working.

To assess the effects of these fare changes, we use two main empirical approaches: a between-city analysis in which we exploit variation in the timing, direction, and magnitude of fare changes in different UberX markets, and a within-city analysis where we compare UberX to Uber's luxury service, UberBlack. UberBlack has generally had constant fares during the period covered by our data.

We view our two empirical approaches as complementary, in that each can partially address the limitations of the other approach. The between-city comparison has the benefit that each UberX market is geographically isolated, minimizing any spill-overs across markets. The downside of this approach is the possibility that cities were selected for fare changes on the basis of their characteristics. However, we find little evidence of this kind of selection, and no evidence of a violation in the parallel trends assumption. With the UberBlack within-city comparison, there is no concern about city-specific selection, but UberX and UberBlack are substitutes, and so spill-overs across markets is a concern, even though we take several steps to address this problem.

Despite their differences, our findings from the between- and within-city analyses are reassuringly similar. We find that when Uber raises the base fare in a city, the driver hourly earnings rate rises immediately, but then begins to decline shortly thereafter. After about 8 weeks, there is no detectable difference in the average hourly earnings rate compared to before the fare increase. With a higher fare, drivers earn more when driving passengers, and so how do drivers make the same amount per hour? The main reason is that driver work intensity falls; drivers spend a smaller fraction of their working hours on trips with paying passengers when fares are higher. Higher fares are also partially "undone" by less frequent and/or more moderate surge pricing (Chen and Sheldon, 2015; Hall et al., 2016). With a higher fare, demand exceeds supply less frequently and by a smaller amount when would-be passengers face a higher price. Note that although we frame our results as effects from a fare increase, we use both fare increases and decreases for identification.

Although both surge and work intensity matter in explaining market equilibration, the change in work intensity is, by far, the more important of the two margins: for a 10% fare increase, the average surge rate would fall by about 2%, but utilization would fall by about 8%. In addition to looking at driver earnings as derived from trip receipts, we also consider the measures of driver earnings that include promotional payments from Uber. We examine how these driver promotional payments—typically payments structured as earnings guarantees for drivers—effect the market adjustment process. We find that guarantees serve as temporary buffers, limiting the "pass through" of fare changes in the short-run, but having no detectable effect in the long-run.

In the period covered by our data, Uber was in many cases the only operating ride-sharing company in a particularly city. However, in some cities, during some periods, Uber faced competition, though none in which the competitor was the market leader. Of course, what Uber offers—transportation services—has a number of substitutes other than transportation network companies. However, the existence of rival ride-sharing firms that offer broadly similar services could make both the supply and demand sides more elastic. This existence could increase the elasticity of demand—passengers can easily switch to alternative services—and elasticity of supply, as drivers could more easily switch between competitive platforms. Despite this possibility, we find very little evidence that scale of competitor had any detectable effect on the adjustment process.

A limitation of our panel analyses is that we can say little about the effects of fare changes on market quantities, such as total rides taken. The core econometric problem is that all of the markets we study are expanding rapidly, albeit at different rates. As such, outcomes such as total rides taken, which are not "scale-invariant," tend to give highly imprecise point estimates in a regression framework that uses the full panel. To address this empirical shortcoming, we also conduct a between-city synthetic control analysis.[1]

For each fare change in our data, we construct a synthetic control city from a donor pool of cities that are broadly similar to the "focal" city experiencing the change. We then assess the quality of each synthetic control by examining how closely it approximates the focal city in the pre-period. Those controls that perform poorly are discarded from the analysis—a luxury afforded by having many fare changes in our data. We then aggregate and scale all of our remaining estimates to give a single estimate analogous to our panel estimates. To first validate our synthetic control approach, we use it with the same outcomes from the within-city and between-city approaches—namely the hourly earnings rate, work intensity and surge. Reassuringly, we find the same pattern of results: no long-run effects on the hourly earnings rate, but persistent changes to both surge and work intensity.

With our synthetic control approach validated, we then use it to estimate the effects of fare changes on market "quantity" outcomes, namely the total number of hours-worked, the number of drivers active, and the total number of trips taken. We find that a fare increase reduces the quantity of trips taken, but has no discernible effect on the number of drivers active. However, total hours-worked declines, implying a labor supply response primarily on the intensive margin rather than the extensive margin. Fewer hours-worked—and lower driver utilization on those hours—explains the decline in trips taken

[1] A city-specific trend could be included, though with a long panel, mis-specification is a concern. As graphical analysis shows that while all city markets were expanding rapidly, the growth was not uniform.

following a fare increase.

Although it might be tempting to interpret the elasticity of trips taken with respect to the base fare as a demand elasticity, it is important to consider that following a fare change, wait times—the time a passenger requesting a ride has to wait until his or her car arrives—could change, shifting the demand curve.[2] Indeed, using our between-city panel approach, we find strong evidence that when the fare increases, wait times fall, despite the goal of surge pricing to keep them more or less constant. The sensitivity of wait times to the base fare is consistent with our finding that a fare increase lowers utilization—with lower average utilization, the nearest car available for dispatch is likely to be closer to the requesting passenger and hence arrives more quickly. Although the changes in wait times are potentially important for explaining how markets adjust, they have little direct import for the driver hourly earnings rate, which is only affected through the surge and utilization "channels."

In terms of generalizability, Our basic set-up—a tightly coupled product and labor market with small firms covers a non-trivial share of the labor market. There are large numbers of sole proprietors and small businesses that have the same basic set-up of workes being paid per job, with the arrival of jobs depending on the total level of demand and supply. Although we show, at least in theory, that these markets would obtain the optimal work intensity, it is far from clear that this simple model

That the decentralized equilibrium does not acheive the effient equilibrium should be no great surprise in a post DMP world (Mortensen and Pissarides, 1999).

Filippas et al. (2018) reports the results of an experiment conducted in a computer-mediated marketplace. The platform substantially raised utilization when it took over centralized pricing. By comparison, NYC Taxi markets—about a thick a taxi market as one can imagine—has an average utilization of TK. During

Search costs bi-lateral monopoly

[2] The effect of a fare change on the average level of surge also poses a problem for demand estimation.

Although Katz and Krueger (2016) finds that alternative work arrangements. Abraham et al. (2017) Documents a substantial rise in self-employment that is more like contract labor Jackson et al. (2017).

We develop a simple product and labor market model with endogenous work intensity. In our model, work intensity is costly to workers and hence affects labor supply. Work intensity is determined in equilibrium and workers only decide whether or not participate at the prevailing wage and intensity. We first show that assuming a decentralized equilibrium product market price and work intensity exists, it would be efficient, in the sense that the value of the output created by a small increase in work intensity would be fully offset by the added cost to workers. At higher product market prices, total surplus could be increased by lowering prices and increasing work intensity—the disutility to workers would be less than the value of the additional output, whereas at any lower product market prices, total surplus would fall.

Our paper makes several contributions. First, our paper illustrates the importance of endogenous work intensity in determining the market equilibrium. It would be impossible to understand the market adjustment in response to fare changes in the absence of information on work intensity.

Although

Second, our findings echo Hsieh and Moretti (2003)—but that paper is about free entry. lots of reasons prices do not float. We should in a labor context.

Mas and Pallais (2017)

Several features of driving with Uber would tend to flatten the labor supply curve, including free entry and exit by drivers, low switching costs to alternative platforms, and relatively low barriers to entry. In contrast, if Uber faces an upward sloping labor supply curve—say, because of its unique flexible offering (Chen et al., 2017), regulatory barriers to entry, non-zero driver fixed costs, income targeting behavior, and so on—the driver hourly earnings rate could be permanently altered following a fare change. If there is a permanent change, the direction of that change is theoretically ambiguous: an increase in the fare—while increasing how much is earned from an hour of driving with passengers—could lower utilization enough to have a net negative effect on the driver hourly earnings rate.

2 Introduction

In the ride-sharing markets created by Uber, the fare schedule faced by passengers is set by Uber, but the hourly earnings rate of drivers is not—it depends not only on how much a driver earns from an hour of transporting passengers, but also on his or her "utilization," or the fraction of working hours that are spent transporting passengers. As such, a driver has an hourly earnings rate that is, mechanically, his or her marginal revenue product. If Uber changes the product market price (i.e., changing the fare), it also changes the driver's marginal revenue product, at least until the market adjusts. The nature of the subsequent market adjustment depends on Uber's relationship to the broader labor market.

If Uber faces a horizontal labor supply curve—as would a small hiring firm in a large labor market—the ride-sharing market should adjust until drivers ar

The key contribution of our paper is to present a clear—and fairly simple—economic account of how the supply-side of a ride-sharing market "works," over the timescale of weeks. We show that when driving with Uber temporarily becomes a better deal, drivers work more and push down hourly earnings through lowered utilization and somewhat less surge. The equilibration process runs in reverse when driving with Uber becomes a relatively worse deal. Drivers, as a whole, appear to be highly elastic in their labor supply with respect to Uber. While drivers clearly value the flexibility offered by the option of driving with Uber (Chen et al., 2017), it is not determinative for the marginal driver and/or the driver considering his or her marginal hour, and so Uber faces a horizontal labor supply curve.

Our finding that total hours-worked declined with a fare increase suggests that, on average, fare *cuts* have made driving for Uber a better deal and that the pre-cut fare was in the elastic portion of the demand curve. A fare reduction made in the elastic portion of the demand curve will tend to raise the driver hourly earnings rate, so long as the supply curve is not perfectly horizontal.

Given our results, a natural question is how many other tightly coupled product/labor markets clear primarily on utilization rather than price. While utilization-driven market clearing seems plausible for many markets and has been observed in some (Hsieh and Moretti, 2003),[3] it is only because of the computer-mediated nature of the markets we study—in which hours-worked and services delivered can be measured essentially without error—that we can illustrate the phenomenon directly. This same computer-mediation gives us the data granularity and frequency to show how equilibration takes place over time. There is typically little theoretical guidance on how quickly market adjustments might take place.[4]

Aside from being an interesting context, ride-sharing markets have grown rapidly, making them *per se* important to understanding urban transport. One implication of our findings is that ride-sharing markets can exist in different equilibria, depending on the fare faced by passengers. All else equal, an equilibrium with a higher utilization is probably socially preferable, given the negative externalities of driving (Parry et al., 2007; Edlin and Karaca-Mandic, 2006).[5] Furthermore, to the extent drivers have fixed costs of entry, the higher utilization equilibrium is preferable for the reasons presented in Mankiw and Whinston (1986). In addition to the importance of the product side of these ride-sharing markets, from a labor market perspective, the kind of computer-mediated market that Uber exemplifies—independent sellers and a

[3] Hsieh and Moretti (2003) show that when housing prices increase, the earnings of real estate agents do not increase much if at all—agents simply sell fewer houses as more agents enter the industry. This is the Uber-equivalent of having fewer rides for some given number of hours-worked, i.e., a lower utilization. Anecdotally at least, workers with qualitatively similar degrees of flexibility to Uber drivers—small business owners, real estate agents, consultants, and freelancers—describe work as being "busy" or "slow"; rarely do they express the sentiment "exactly the same level of business as always, but at fluctuating prices."

[4] Some have argued that the speed of adjustment is critical for the monopsony versus competitive characterization of labor markets (Manning, 2003; Kuhn, 2004).

[5] Though this claim must be tempered by the higher cost drivers presumably have at higher levels of utilization.

mediating platform with some market design powers—seems likely to become more common in the future with the rise of the so-called "gig economy" (Katz and Krueger, 2016). Our paper illustrates the relationship of one such market to the larger labor market.

The rest of the paper is organized as follows. Section 3 describes the empirical context. Section 4 presents a simple model and discusses some of the prior work on taxi markets. Section 5 presents the empirical results. Section 6 discusses the results and concludes with some thoughts on the implications of our results for Uber's pricing problem.

3 Empirical context

Uber connects passengers with drivers-for-hire in real time, creating a collection of city-specific, geographically-isolated markets. It currently operates in more than 340 cities, in over 60 countries. The core products of Uber are UberBlack and UberX. UberBlack is the premium option, with newer, more luxurious cars and drivers that meet other conditions. UberX is the peer-to-peer option and is the largest and fastest growing Uber product. It is also available in more cities that UberBlack (see Hall and Krueger (Forthcoming) for a discussion of the relative size of the two services). Regardless of the product, passengers use the Uber app to set their location and request a ride. These trip requests are sent to the nearest available driver. At the end of the trip, the fare is automatically charged to the passenger's credit card. Uber handles all billing, customer support, and marketing.

The price of an UberX and UberBlack trip depends on a number of parameters set by Uber. There is a per-minute time multiplier and per-mile distance multiplier, as well as a fixed initial charge, as well as service fees in some markets. To calculate the actual fare paid by the passenger, the parameters are multiplied by the realized time and distance of a trip, which is then multiplied by the surge multiplier that was in effect when the trip was taken. The surge multiplier is set algorithmically in response to wait times, with the intent of inducing supply and rationing demand in order to keep those wait times from increasing too much. During "un-surged" periods, the multiplier is 1.0.[6] There is a minimum charge that applies if the calculated fare is below that minimum. Recently, Uber has begun using "up-front" pricing in which passengers are quoted a fare at the start of the trip, based on the expected values for the distance and duration, given the user-provided trip start and end points. During the period covered by our data, the identifying variation in the base fare comes before up-front pricing was widely implemented.

As we will see, Uber has changed the time and distance multipliers for UberX in every city in our data. When Uber has made a change in a given city, it has typically changed the time and distance multipliers by the same percentage. To avoid the complexity of tracking different fare components separately, we construct price indices. For a given service (i.e., UberX or UberBlack), city and week, the index is the total fare for an un-surged 6 mile, 16 minute trip. This trip is approximately the median trip time and distance for the US.

We explore how changes in the price index affect a variety of market outcomes. Our primary outcome is the average hourly earnings rate of drivers, which is the total weekly driver revenue divided by the total hours-worked. This method is equivalent to averaging all driver-specific estimates of the hourly earnings rate and weighting by individual hours-worked.

For driver revenue, we omit reimbursements for known tolls and fees (such as airport fees), and deduct Uber's commission. We do not calculate drivers' costs, and so it is important to regard our measure of the hourly earnings rate as a gross flow to both the driver's labor and capital, without costs subtracted. For driver hours-worked, we define hours-worked as the total time a driver spent "online" with the Uber platform, which includes all time on-trip, en-route to pick up a passenger, or simply being available for dispatch. Merely having the app open without marking oneself available for dispatch does not contribute to our measure of hours-worked.

Our definition of hours-worked does not perfectly capture what we might

[6] Cohen et al. (2016) uses variation in surge pricing to estimate the elasticity of demand for UberX at several points along the demand curve.

think of as working. For example, some drivers make themselves available for dispatch while "commuting" to where they normally seek passengers (such as the central business district in a city), increasing our hours-worked and decreasing our estimate of the hourly earnings rate. Drivers also report driving with multiple ride-sharing platforms simultaneously, turning one app off immediately after being dispatched by the other platform. This multi-homing strategy will also tend to inflate hours-worked and thus lower the implied hourly earnings rate. However, as our interest is primarily in changes in driver hourly earnings, so long as these definitional biases do not change with the fare, they are of secondary importance.

Drivers are eligible for promotional payments that typically depend on meeting various goals, such as hours-driven or rides-taken in a week. For our initial analysis, we do not include any driving-related promotional payments in our definition of the hourly earnings rate. When we do explore the effects of promotional payments, we allocate the payments as earnings in the week in which they were paid. Some promotional payments unrelated to driving, like those earned for referring another driver, are omitted from the numerator.

3.1 Data description

We construct a panel of 43 US cities over 105 weeks, beginning with the week of 2014-06-02 and ending with the week of 2017-01-16. All cities in the panel have an UberX service, though only some have UberBlack. We started with the 50 largest US cities by total trip volume and then removed from the panel cities which had substantial changes to the areas of service availability or significant within-city geographical variation in pricing.[7] These cities include Boulder, Denver, Indianapolis, Las Vegas, Philadelphia, and the "cities" of Connecticut, New Jersey, and Greater Maryland, which were managed as cities in Uber's system but did not in fact represent single markets. The panel is

[7]The 50 city starting point is, of course, somewhat arbitrary, but this cutoff ensures a long panel of cities with substantial markets. As it is, not all cities in our panel are complete because even the top 50 includes several markets that were not very mature in the start of the panel.

slightly unbalanced in that we lack early data for Portland, Charleston, New Orleans, and Richmond because these cities had relatively late introductions of UberX. The panel begins with the week in which driver earnings data is first reliably available; prior to 2014-06-02, historical driver earnings cannot be reconstructed with sufficient confidence.

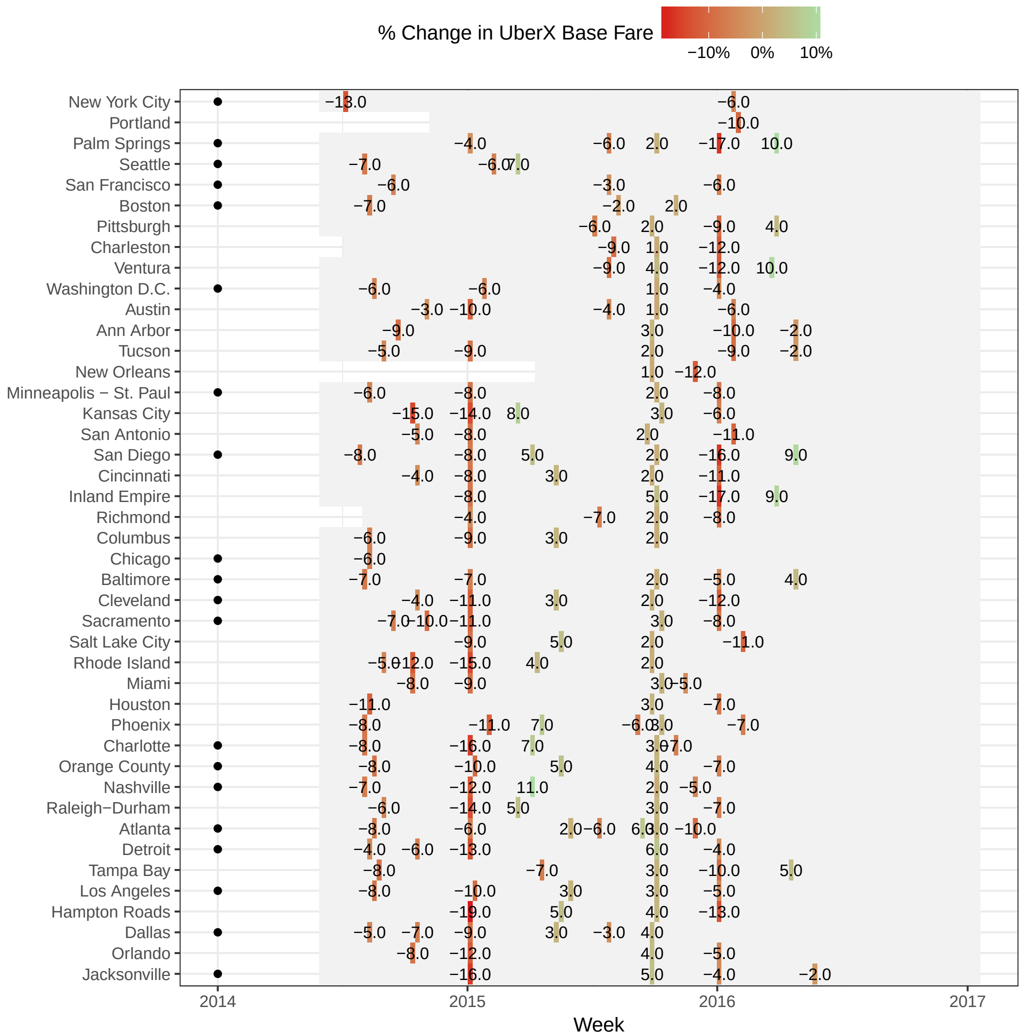
3.2 Variation in the base fare index

Uber has changed the base fare for UberX in every city in the panel, with nearly all cities experiencing multiple changes. Figure 1 highlights the weeks in which the UberX base fare index changed for the panel cities and reports the size of the change. A grey tile indicates no change occurred that week. Cities are listed in descending order of their average base fare over the period. A black dot next to the city's name indicates that that city had an UberBlack service.

The decision to change the fare in a city was made after consultation with the Uber employees responsible for the city in question. They were advised by Uber's internal "pricing team," which reportedly considered metrics like driver utilization and the fraction of trips taken under surge conditions. For our purposes, this creates an obvious selection concern, though we will argue that there are several justifications for treating fare changes as exogenous for our between-city comparison purposes. Furthermore, our fine-grained time scale makes the parallel trends assumptions readily assessable.

There are several justifications for treating fare change variation as exogenous. First, we first note that as every city in the panel had fare changes, it is not the case that latent differences exist between the kinds of cities that have fare changes and those that do not. Second, Figure 1 shows that many changes took place in numerous cities nearly simultaneously, making it clear that highly city-specific explanations were not driving many of the fare changes. Note that in both 2015 and 2016, many cities experienced large cuts in the base fare right after the start of the new year. There are several cases in the data where cities all have fare changes within a fairly small window, but the precise timing dif-

Figure 1: UberX base fare index changes for US cities, by week



Notes: This figure indicates which cities in the panel had changes in the base trip price index, by week, and reports the size of that change, in percentage terms relative to the fare in the previous week. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The x-axis is in weeks. Whether the city had a viable UberBlack service is indicated by a dot next to the city name. Squares that are not shaded gray indicate that no data is available for that city week. Cities are listed in descending order of their average base fare over the entire panel. See Section 3.1 for a definition of the sample.

fers by only a few weeks—it seems unlikely that the precise sequence of cuts reflects important latent differences.[8] Finally, leaks by various media sources indicate that a relatively simple spreadsheet-based analysis was used to model city outcomes, making it doubtful that decision-makers were confidently conditioning on future potential outcomes.

To the extent cities were selected for fare changes on the basis of observable attributes, we know approximately what those attributes are, and we can look for pre-treatment trends in those outcomes. In addition to checking for evidence of selection, our UberBlack within-city research design is not subject to the same concern that latent city-specific factors were the cause of fare changes, as is the case with the between-city design. In Appendix A, we report an analysis in which we use our observed data to model Uber's city and fare change selection and magnitude and simulate counter-factual fare changes. We find that for all our outcomes, the distribution of these counterfactual placebo fare changes are centered at 0 and far away from our realized non-zero point estimates.

4 Conceptual framework

In this section, we present a simple model of a combined product/labor marketplace where work intensity can vary.

There is a product market price, p, which determines demand $D(p)$, with $D'(p) > 0$. Workers have an equilibrium work intensity x. Workers have some utility $u(w, x)$ and an idiosyncratic reservation wage that collectively create a labor supply curve with respect to the utility of the representative worker, or $S(w, x) = S(U(w, x))$. We assume that $\partial U/\partial w > 0$ and $\partial U/\partial x < 0$, and that $S'(\cdot) > 0$.

In Figure 2, we draw a collection of worker indifference curves. The y-axis is the market wage and the x-axis is the work intensity. As work intensity is

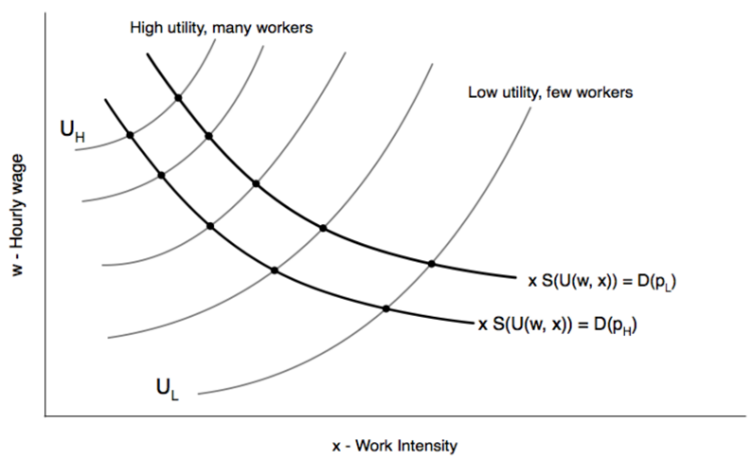
[8] However, fare changes also differed in magnitude and not just timing, and so there is a non-time related exogeneity concern. We have no insight into how the precise percentages were chosen for various cities.

costly, for every curve, an increase in x requires a corresponding increase in w to keep workers as satisfied, and hence to keep labor supply constant. As we move toward the upper left, utility—and hence hours-worked increases.

Market clearing requires that $D(p) \equiv xD(S(U(w,x)))$.

In the figure, in heavy lines, we indicate possible equilibria for two different product market prices, p_L and p_H. At p_H, there is less demand and so for a given number of hours-worked, a lower utilization is needed to clear the market. This is why the p_H-defined curve is everywhere underneath the p_L-defined curve.

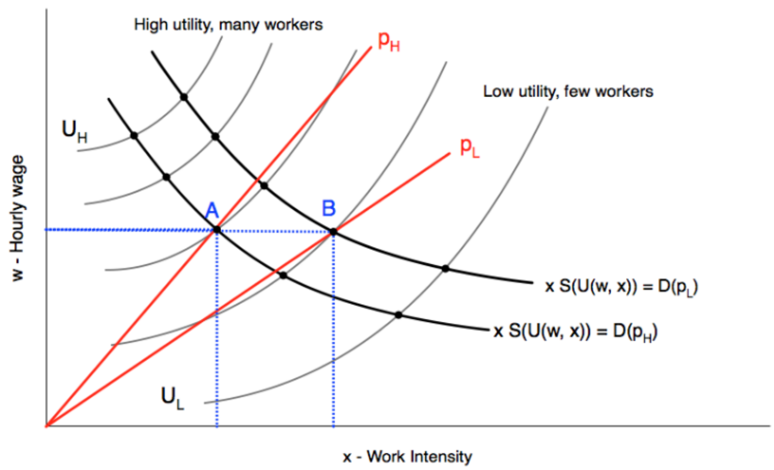
Figure 2: Possible work intensity equilibria



Notes:

Although these equilibria are all possible, only one is consistent with workers earning their marginal revenue product—namely one in which $w = px$. In Figure 3, we illustate two equilibria, A and B that satisfy this condition, corresponding to p_H and p_L. The two lines labeled p_L and p_H have slopes of p_L and p_H and both start at the origin. As such, the point where they intersect the corresponding heavy-line curves of possible equilibria indicates an equilibrium, as the height of the curve at the intersection for a curve is px, which is require wage for that particular work intensity. As drawn, the low price equilibrium has a higher work intensity but a wage that is the same as in the high price equilibrium, A. As such, the workers in this equilibrium have a lower utility.

Figure 3: Wage and work intensity indifference curves



Notes:

A natural question is what would be the efficient equilibrium for a given supply and demand curve. Intuitively, we would want work intensity to increase until the marginal increase in intensity would produce output of value equal to the cost to the workers. This point is actually where the product market price curve p is tangent to the worker indifference curve. To see why, on any indifference curve, the slope is

$$\frac{\mathrm{d}w}{\mathrm{d}x} = \frac{\partial U/\partial x}{\partial U/\partial w}. \tag{1}$$

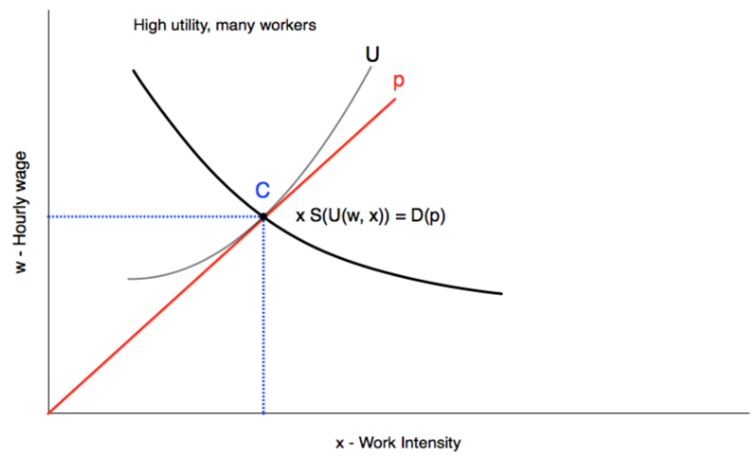
and so when the price curve is tangent,

$$\mathrm{d}w = p\,\mathrm{d}x \tag{2}$$

, which is, on a per-worker basis the optimality condition stated above: a small increase in work intensity, $\mathrm{d}x$, produces $\mathrm{d}xp$ more output, but costs the worker $\mathrm{d}w$ (recall that we are moving along an indifference curve). If we return to

Figure 3, we can see that both A and B are inefficient as drawn because they are not tangent to their respective indifference curves. For A, $\mathrm{d}w < p\,\mathrm{d}x$, and so the greater work intensity produces output greater than the cost to the worker, whereas the opposite is true for B. Figure 4 shows the optimal equilibrium wage.

Figure 4: Optimal



Notes:

They collectively supply $S(w, x)$ hours of labor when the market wage is w and the utilization x.

The model illustrates the potential margins of adjustment in response to a change in the base fare. There are extant models of taxi markets, but they tend to focus on the micro details of search and matching, and the unique market properties this search process generates, such as non-existent/multiple equilibria or industry scale economies. The unique features of ride-sharing markets—such as dynamic pricing and centralized algorithmic dispatch—make many of these search considerations less important, and so we develop our own simple model. However, we do briefly review this literature before presenting our model.

Arnott (1996) presents a model of a "cruising" taxi market (as opposed to one with centralized radio dispatch), focusing on the potential for scale economies in the industry, which in turn might justify subsidization. Castillo et al. (2017) build on this work, exploring the role of dynamic pricing in avoiding highly inefficient equilibria. Cairns and Liston-Heyes (1996) present a model in which both sides of the market search for each other, showing that competitive equilibrium does not necessarily exist.[9] Frechette et al. (2015) present a calibrated equilibrium model of the NYC taxi market, with a focus on matching frictions and their role in determining the market equilibrium.

In the "old" models of the taxi industry discussed above, passenger demand depends on wait times, which adds substantial modeling complexity. We can pursue a simpler modeling approach—namely using a single demand curve—because dynamic pricing is intended to prevent the market from clearing on wait times.[10] Our treatment of driver labor supply is also simple, ignoring behavioral considerations, such as income targeting (Camerer et al., 1997) and even whether labor supply changes are due to extensive or intensive margin adjustments. Rather, we assume that labor supply can be captured with a single supply curve of total hours-worked.[11]

Market clearing in our model is not the result of drivers deciding to extend shifts or passengers forgoing a surged trip, but rather about drivers deciding how much to drive with Uber over the course of weeks and passengers deciding

[9]Both supply and demand are determined by the wait time (either for the cab on the passenger side, or for the next fare, on the supply side) and the fare, and the market could clear at a number of different equilibria.

[10]See Hall et al. (2016) for evidence on the role of Uber's surge pricing in clearing the market when demand spikes. See Castillo et al. (2017) for a discussion of the importance of surge pricing to prevent nearly discontinuous changes in wait times when demand outstrips supply.

[11]There is some evidence that behavioral labor supply considerations are relatively unimportant. Farber (2005, 2008) argues that income targeting findings are mostly due to division bias, and that driver behavior is mostly consistent with the neoclassical labor supply model. Errors in the measurement of hours-worked tend to attenuate an estimate of the labor supply since the hours measurement is also used to calculate the wage. A key advantage of our empirical setting is that we can measure hours-worked essentially without error. Farber (2015) shows that there is substantial heterogeneity in individual labor supply elasticities and that drivers that do not learn to work more when wages are temporarily high are not long for the taxi driving profession. Using data from Uber, Chen and Sheldon (2015) also present evidence that Uber driver's are responsive to hourly earnings in a neo-classical fashion and that there is little evidence of income targeting. Also using data from a Uber, Angrist et al. (2017) also find no evidence of income targeting.

how many hours of transportation service to buy over the course of weeks, in response to the average prices they will experience. Our model ignores the micro details of real-time market clearing, and should be thought of as describing a market over the course of weeks or months.

4.1 Model

Passengers demand hours of transportation services. The price per hour of transportation services is p, which is the base fare, b, times the average surge multiplier, m, and so $p = bm$. There is demand for hours of transportation, $D(p)$, with $D'(p) < 0$. The quality of transportation services is constant and unrelated to any other features of the market. Homogeneous drivers have an hourly earnings rate of w and collectively supply $S(w)$ hours of *work*, with $S'(w) > 0$. Hours of work are turned into hours of transportation at a rate x, where x is the fraction of hours-worked drivers spend on trips carrying passengers. Market clearing requires that

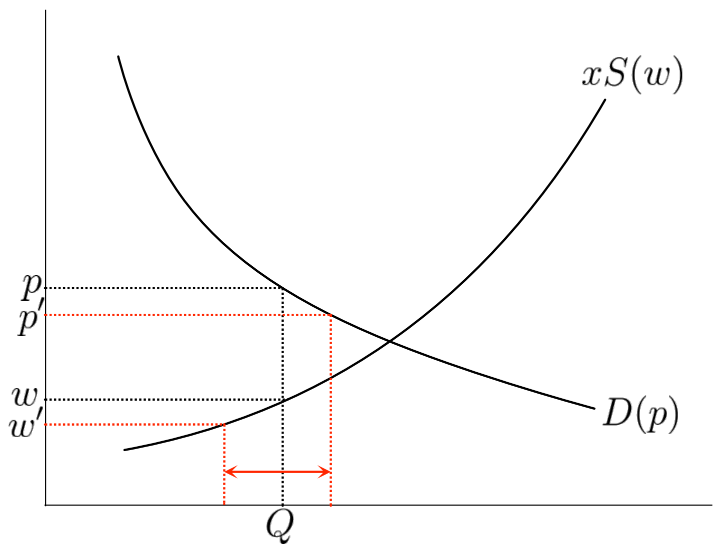
$$D(p) = xS(w).$$

The average hourly earning rate of drivers is simply the price times the utilization, or $w = px$. Figure 5 shows a market initially in equilibrium at some base fare p and hours of transportation services Q.

Now we consider the comparative statics of this market with respect to the base fare. Uber does not change p directly, but rather changes b, which in turn can change m in equilibrium. Suppose Uber lowers the fare by $\mathrm{d}b$, causing the fare faced by passengers to change by $\mathrm{d}p = m\,\mathrm{d}b$. At this new price $p' = p - \mathrm{d}p$, there are $\mathrm{d}pD'(p)$ more hours of transportation demanded. Before x or m adjusts, the hourly earnings rate falls to $w' = w - \mathrm{d}px$, reducing hours driven by $S'(w)\,\mathrm{d}w$ and hence hours of transportation by $xS'(w)\,\mathrm{d}w$. This gap between what is demanded and what is supplied is $\mathrm{d}p\left(D'(p) - xS'(w)\right)$, which is indicated in Figure 5 with a double-headed arrow. To connect our model to our empirics, our main research question is how this gap is closed.

Our first question of interest is what happens to the driver hourly earnings

Figure 5: Equilibrium in a ride-sharing market after a decrease in the base fare



Notes: The $D(p)$ curve is the market demand for hours of transportation service, when the price, or fare, is p. The $S(w)$ curve is the hours of work supplied and $xS(w)$ is the hours of transportation services provided, where w is the driver hourly earnings rate and x is the driver utilization. Q is the market equilibrium quantity of hours of transportation service before a fare change. This figure illustrates the effects of a reduction in price from p to p' before any equilibrium adjustment. The double-headed arrow indicates the gap between hours-supplied and hours-demanded of transportation services following the fare change.

rate when the base fare changes. We assume, for now, that the surge multiplier is fixed and that adjustment can only occur through changes in utilization. Proposition 1 gives an answer to this adjustment question in terms of the labor supply and transportation demand elasticities.

Proposition 1. *If the market only clears on driver utilization, the elasticity of the driver's hourly earnings rate, w, with respect to the fare, p, is*

$$\epsilon_p^w = \frac{1 + \epsilon_p^D}{1 + \epsilon_w^S}.$$

Proof. The elasticity of the driver's hourly earnings rate with respect to p is $\epsilon_p^w = 1 + \epsilon_p^x$. The elasticity of utilization with respect to p can be derived from the market clearing requirement. Differentiating $D(p) \equiv xS(w)$ by p, we have $\epsilon_p^D = \epsilon_p^x + \epsilon_w^S \left(1 + \epsilon_p^x\right)$, and so

$$\epsilon_p^x = \frac{\epsilon_p^D - \epsilon_w^S}{1 + \epsilon_w^S}.$$

□

Increasing utilization works both "inside and outside" the supply curve to help clear the market, by making each hour supplied more productive, but also by causing movement along the curve as drivers respond to the higher hourly earnings rate.

It immediately follows from Proposition 1 that when drivers are infinitely elastic, hourly earnings cannot fall, as $\epsilon_w^S = \infty$ implies that $\epsilon_p^w = 0$. If drivers have finite labor supply elasticities, then the direction of the effect of a fare change on the hourly earnings rate depends on the demand elasticity. Conditional upon a finite labor supply elasticity, if $|\epsilon_p^D| > 1$, an increase in the fare will lower the hourly earnings rate, and vice versa when $|\epsilon_p^D| < 1$. The intuition is that with elastic demand, changes in the fare cause large shifts in the hours of transportation demanded, which in turn affects driver utilization enough to more than offset the direct effect of the fare change on the hourly earnings rate.

Proposition 1 only considers adjustments in x as the means to clear the market. However, as Figure 5 illustrates, there are other ways for the market to clear. First, the average surge multiplier can increase, essentially "undoing" the fare change. Second, the supply curve could be shifted out, say due to more aggressive driver recruitment. Third, the demand curve could be shifted in, say because of increased wait times. Each of these adjustments would help close the gap shown in Figure 5. We will investigate all three of these margins empirically.

Our assumption that labor supply is fully captured by $S(w)$ implies that

x does not does not enter separately into driver decision-making potentially. In practice, with a higher utilization, drivers would face somewhat higher per-hour costs from a higher x through higher gas expenditure (both because they have a passenger in the car, which reduces fuel efficiency, and because they cannot park and simply wait for dispatch), increased vehicle wear-and-tear, increased cleaning expenses, and so on.

If we assume that costs are linear in x, i.e., $w = (p - c)x$, with $c > 0$, Proposition 1 would still hold, but to the extent that there is individual driver heterogeneity in c, those drivers that find a higher utilization equilibrium relatively less costly would be inframarginal, leading to a compositional shift in which drivers are marginal at different equilibria.

5 Results

In this section, we present both the between-city (UberX to UberX) and within-city (UberX to UberBlack) estimates of the effects of base fare index changes on market outcomes. Our outcomes of interest are the driver hourly earnings rate—w in the model—and its endogenous components, utilization and the surge multiplier, which are x and m in the model, respectively. Recall the $w = bmx$, where b is the base price.[12]

After reporting the panel results, we present synthetic control estimates for the same outcomes used in the panel analysis—hourly earnings, utilization, and surge—as well as for market quantities, namely the number of trips taken, the total hours-worked, and the number of active drivers. We then return to the between-city panel to explore the effects of fare changes on passenger wait times.

[12]Our constructed price index is not exactly b, which in the model is the cost of an hour of transportation services. Our index is instead the price for a standard trip, which we could convert to a time-based rate by dividing by the duration. However, this distinction is immaterial for our purposes, as we will be using the log of our price index as an independent variable.

5.1 Panel-wide averages over time

Before presenting the panel regression results, we first simply plot the weekly averages for the base fare index and our outcome measures, pooled over all cities in the panel. Figure 6 shows, from top to bottom, the mean base price index, hourly earnings rate, utilization, average surge, and median wait time. All series are normalized to have a value of 1 in the first period of the panel.

In the top panel, we can see that there has been a long-run decline in the price index, though it has not been strictly monotonic. In the panel below, we see that during that same period, the hourly earnings rate time series exhibits no similar trend. In contrast, driver utilization has increased substantially over the same period. There is little systematic change in average surge levels. In the bottom panel, we see that wait times were high early in the panel, but fell substantially by early 2015 and then are more or less constant afterwards.[13]

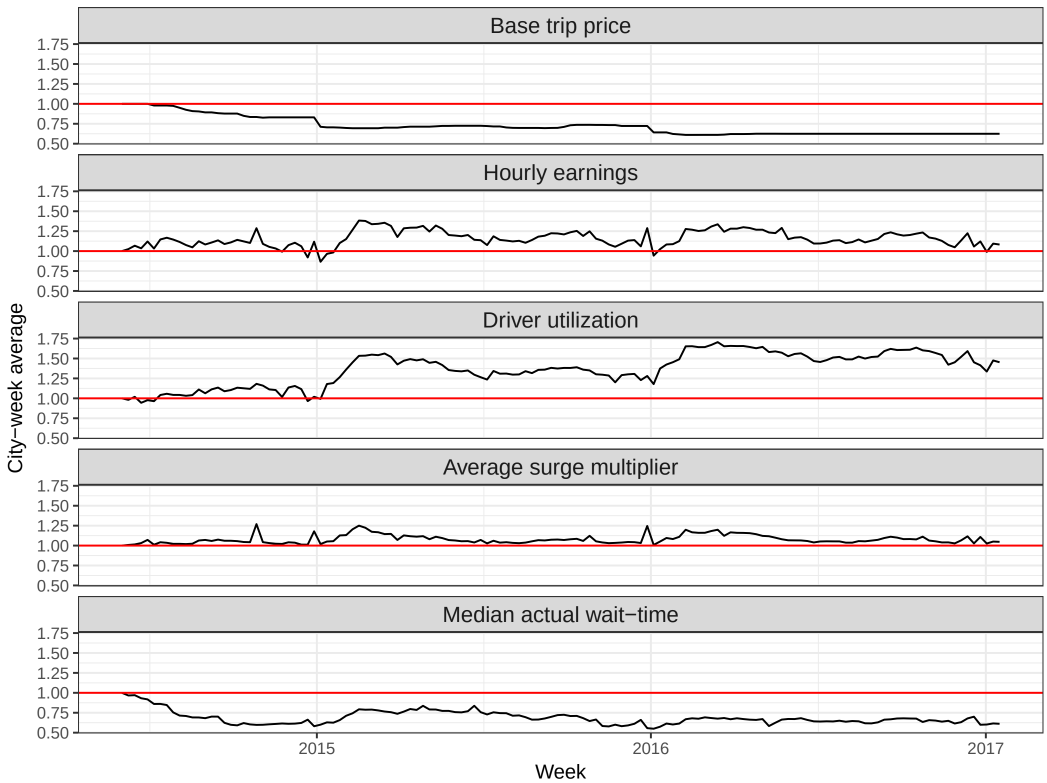
The patterns shown in Figure 6 preview some of the main results from our regression analysis—namely little change in the hourly earnings rate despite large changes in the base fare index. Note that the two large drops in the base fare index occur at the start of 2015 and 2016. Immediately after, average surge increases, as does utilization, though only utilization seems to show a persistent change in levels. The driver hourly earnings rate series appears more or less stable, as does the median wait time series (following a decrease in early 2014).

5.2 Between-city approach

To begin our estimation of the causal effects of fare changes, we first set aside the possibility that market adjustment takes time and simply report "long-run" estimates of the effects of fare changes, assuming that the full adjustment

[13] Note that we use the median wait time in a city week as opposed to the mean, as wait times are trip level measures and subject to outliers.

Figure 6: Average UberX market attributes over time for the US city-week panel, as indices



Notes: This figure plots the city-week panel weekly average for a collection of UberX market outcomes. All cities are weighted equally—see Section 3.1 for a definition of the sample. All series are turned into an index with a value of 1 in the first week. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Surge is the average value of the multiplier for all trips conducted in that city, during that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. The wait time for trip is the elapsed time from when a passenger requested a trip to when he or she was picked up.

occurs immediately.[14] Our specification is

$$y_{it} = \alpha_i + \beta_1 \log b_{it} + \beta_2 (\log b_{it} \times t) + \gamma_i t + \delta_t + \epsilon_{it}, \tag{3}$$

[14]This specification is sometimes called the "static" specification—see Borusyak and Jaravel (2016) and references therein.

where y_{it} is some market-level outcome of interest in city i during week t, where α_i is a city-specific fixed effect, γ_i is a city-specific linear time trend δ_t is a week-specific fixed effect, and b_{it} is the base trip price index, which has a common coefficient β_1. Note that we also also for a price-level specific common time trend, β_2.

Table 1 reports estimates of Equation 3 where the outcome variables are the log hourly earnings rate, log utilization, and log surge in Columns (1), (2) and (3), respectively. For each regression, standard errors are clustered at the level of the city.[15]

From Column (1), we can see that an increase in the base fare decreases the hourly earnings rate, though the effect is close to zero, with a confidence interval that comfortably includes zero. The point estimate implies that a 10% increase in the base fare would lower driver hourly earnings by a little less than 1%. From Column (2), we see part of the explanation for why hourly earnings do not increase—a higher fare reduces utilization, with a 10% increase in the base fare reducing utilization by about 8%. Finally, in Column (3) we can see that the rest of a 10% increase in fares is approximately undone by about a 2% decrease in the average surge multiplier.

To explore how the market adjusts over time, we need a more richly specified regression model with lag and lead indicators around fare changes (Autor, 2003). Let $\textsc{FareChange}^{\tau}_{it}$ be an indicator for whether at time t, the base fare in city i is different than it was τ weeks earlier or later. To "cherry pick" the week when a fare change occurred/will occur exactly τ weeks away from the current week, we define an indicator

$$z^{\tau}_{it} = \textsc{FareChange}^{\tau}_{it} \prod_{s=0}^{\tau} (1 - \textsc{FareChange}^{s}_{it}).$$

[15] We also conducted a block bootstrap at the city level to test for Bertrand et al. (2004) problems, but we found that the bootstrap standard errors were almost identical to the clustered standard errors, and so we only report clustered standard errors.

Table 1: Effects of fare changes on market outcomes from a city-week panel of UberX markets

	Dependent variable:		
	log hourly earnings rate	log utilization	log surge
	(1)	(2)	(3)
Log base fare index	0.089	-0.688^{***}	-0.149^{***}
	(0.092)	(0.087)	(0.047)
Log base fare index × t	-0.001	0.0001	-0.002^{**}
	(0.002)	(0.002)	(0.001)
City FE	Y	Y	Y
City-specific linear trend	Y	Y	Y
Week FE	Y	Y	Y
Observations	5,852	5,852	5,852
R^2	0.749	0.817	0.473
Adjusted R^2	0.739	0.810	0.453

Notes: This table reports OLS regressions of city-week outcomes on the log base fare index. The estimating equation is Equation 3. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The sample for each regression is the same, and is a city-week panel of UberX markets. See Section 3.1 for a description of the sample. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week. Fixed effects are included for the city and for the week. Standard errors are clustered at the level of the city. Significance indicators: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

We can then estimate

$$y_{it} = \beta_{\mathrm{LR}} \log b_{it} + \sum_{\tau=A}^{B} \beta_\tau z_{it}^\tau \Delta \log b_{it}^\tau + \gamma_i + \delta_t + \epsilon_{it}, \tag{4}$$

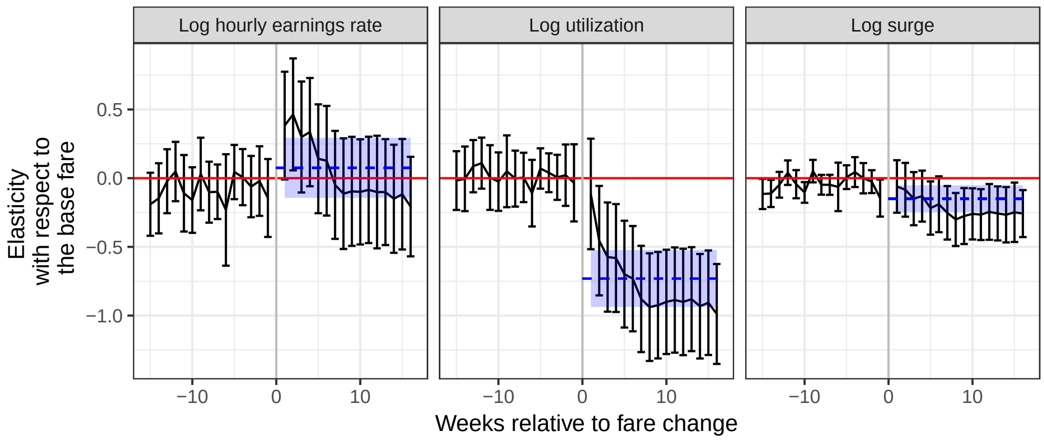
where b_{it} is the fare index in city i at time t, $\Delta \log b_{it}^\tau$ is the difference (in logs) between the current fare index and the fare index τ weeks prior or later (depending on the sign of τ), δ_t is a week-specific fixed effect and γ_i is a city-specific fixed effect. The number of pre-period week indicators is A and the number of post-period weeks indicators is B. The estimated effect for a fare change that occurred τ weeks ago is $\hat{\beta}_{\mathrm{LR}} + \hat{\beta}_\tau$ if $\tau \in (0, B]$, otherwise the estimate is just $\hat{\beta}_{LR}$. The coefficients for the pre-period can be used to assess whether the cities selected for fare changes were systematically different, or on different trajectories, with respect to the outcome.

The implied weekly effects from Equation 4 are plotted in Figure 7 for each of the same outcomes as used in Table 1. The outcomes are the log hourly earnings rate, log utilization, and log surge, using $A = B = 15$. For each outcome, the long-run effect from Table 1 is plotted as a dashed horizontal line in the post-period.

From the left-most panel of Figure 7, we can see that following a fare increase, the driver hourly earnings rate increases immediately, though there is considerably less than full pass-through; the point estimate is only about 0.5. In the weeks that follow, this increase in the hourly earnings rate declines, with the point estimate turning negative by week 8, after which it is close to the long-run estimate from Table 1. Examining the pre-period, there is no obvious trend in the collection of coefficients. However, in most periods, the point estimate is greater than zero, though for nearly all point estimates, the 95% confidence interval includes zero.

In the next panel to the right, the outcome is the log driver utilization. Following a fare increase, utilization gradually falls. By week 8, the effect is close to the estimate of the long-run effect, which was an 8% decrease in utilization for a 10% increase in the base fare index. In the pre-period, there is no evidence of a trend, though in all cases, the utilization point estimate

Figure 7: Between-city estimates of the by-week market adjustments to a change in the UberX base fare index



Notes: This figure plots the by-week effects of changes in the UberX base fare on several market outcomes, namely the log hourly earnings rate, the log average utilization, and the log surge. These effects are from an OLS estimation of Equation 4. The sample is a panel of US cities—see Section 3.1 for a description. The x-axis are weeks relative to a fare change. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week. The horizontal dashed blue line in the post period indicates the "long-run" effect corresponding to Equation 3. Fixed effects are included for the city and for the week. 95% CIs are shown for each point estimate and standard errors are clustered at the city level.

is somewhat greater than zero, consistent with Uber targeting cities for fare increases that had relatively higher utilization, or, equivalently given our empirical specification, targeting cities for fare cuts that had relatively lower utilization.

In the next panel to the right, the outcome is the log average surge. The average multiplier gradually declines following a fare increase. However, the long-run estimate is still somewhat closer to zero than the 15 week point estimate, suggesting the market has not fully adjusted by week 15. There is no obvious trend in the pre-period and the pre-period weekly point estimates are all close to zero (and not consistently above or below).

5.3 The role of promotional payments

Uber has, in some markets, paid promotional payments to drivers. Many of these payments are various forms of earnings guarantees; typically, if drivers drive some minimum number of hours, they are guaranteed to make at least some floor amount. Given their structure, we might expect these guarantees to act as automatic stabilizers, counteracting the immediate effects of a fare change on "organic" earnings.

To explore the role of these promotional payments on market adjustment, in Figure 8, we plot the effects of a fare increase on two measures of the hourly earnings rate: without promotional payments included, in the first panel, and with promotional payments included, in the second panel. We also report the effects of the fare change on the fraction of hourly earnings that are due to promotional payments in the third panel.

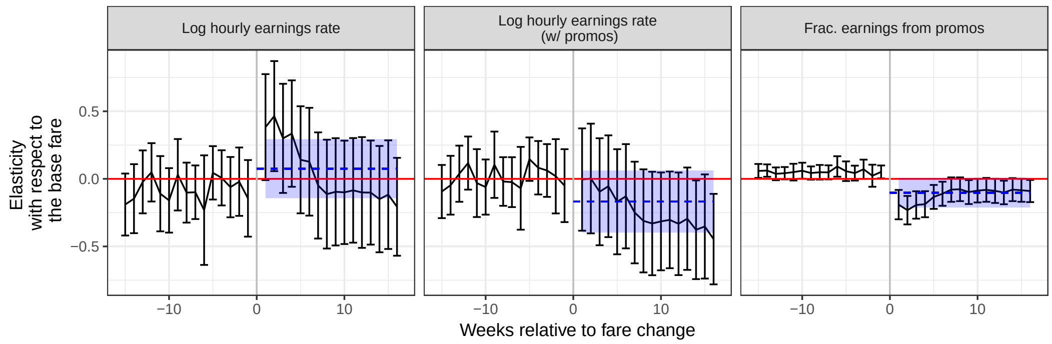
Comparing the two leftmost panels, we see that promotional payments do seem to "soften" the effects of fare changes. For example, the pass-through immediately after the fare increase is about 0.5 for the organic hourly earnings rate, whereas it is only 0.3 when promotional payments are included. In the rightmost panel, we can see that the fraction of earnings from promotional payments drops immediately after a fare increase. This is why the hourly earnings rate with promotional payments "peak" is below the organic measure.

Despite the short-run point estimate differences, we can see that the long-run effect of promotional payments is close to zero. Promotional payments prevent extreme short-run hourly earnings rate fluctuations, but appear to have negligible long-run effects, with the long-run being only about 8 weeks.

5.4 Passenger wait times

As we discussed when presenting the model in Section 4, one way the market could clear following a base fare change was a *shift* in the demand curve, rather than movement along the demand curve. One demand curve shifter could be passenger wait time. In Figure 9, we report panel estimates of the effects of a fare change on passenger wait times, with lower wait times being

Figure 8: Effects of fare changes on hourly earnings with and without promotional payments included



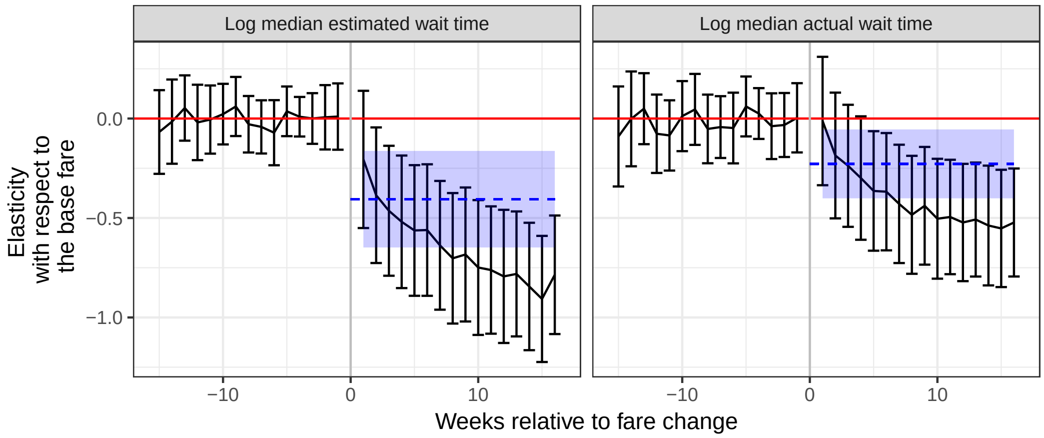
Notes: This figure plots the effects of changes in the UberX base fare index on three outcomes (from left to right): (1) the log hourly earnings rate not including promotional payments, (2) the log total hourly earnings rate includes promotional payments, and (3) the fraction of hourly earnings coming from promotional payments. These effects are from an OLS estimation of Equation 4. The sample is a panel of US cities—see Section 3.1 for a description. The x-axis are weeks relative to a change in the base fare index. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The horizontal dashed blue line in the post period indicates the "long-run" effect corresponding to an estimation of Equation 3. Fixed effects are included for the city and for the week. 95% CIs are shown for each point estimate and standard errors are clustered at the city level.

preferred to longer wait times by all would-be passengers. In the left panel, the outcome is the log median expected wait times (which Uber reports to would-be passengers), and in the right panel, the log median actual wait times.

Figure 9 shows that increases in the fare caused both predicted and actual wait times to decline. The effects are substantial, with a 10% increase in fares reducing wait times by about 5%. The reason for this change is presumably that with less demand and/or lower driver utilization, for a given would-be passenger requesting a ride, the nearest empty car is likely to be closer (so long as the number of drivers does not decrease). As we will see later, there is little evidence of a change in the number of drivers following a fare change, and so it seems likely that changes in wait times are wholly explained by changes in utilization. Note that there is some evidence of targeting, with higher wait times in cities that experienced fare increases.

Changes in wait times have no direct bearing on the driver hourly earnings

Figure 9: Effects of fare changes on predicted and actual log median wait times



Notes: The outcomes in this panel are the log wait times (in seconds), both predicted by Uber (in the left panel) and the realized wait times (in the right panel). These effects are from an OLS estimation of Equation 4. The sample is a panel of US cities—see Section 3.1 for a description. The x-axis are weeks relative to a change in the base fare index. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The horizontal dashed blue line in the post period indicates the "long-run" effect corresponding to an estimation of Equation 3. Fixed effects are included for the city and for the week. 95% CIs are shown for each point estimate and standard errors are clustered at the city level.

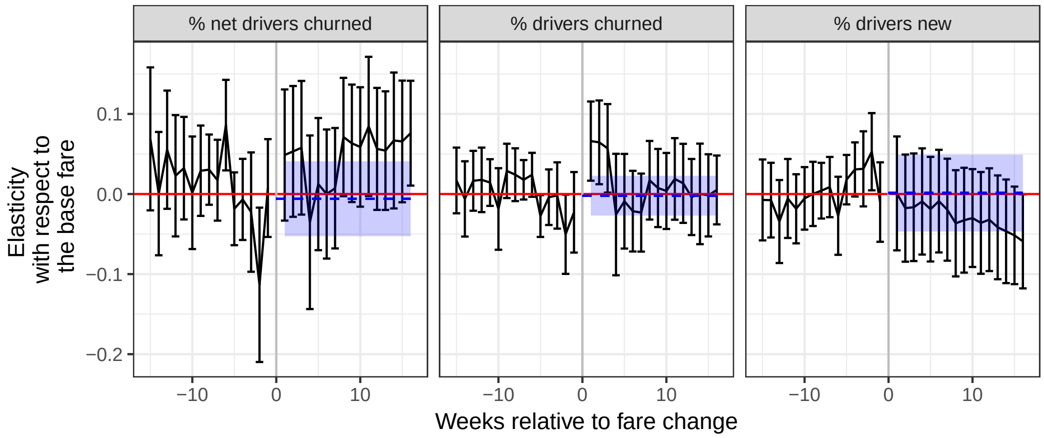
rate. However, they do suggest that ride-sharing markets adjust in part by a shifting of the demand curve following a fare change. Contrary to our modeling assumption in Section 4, surge pricing does not, as implemented during the period covered by the experiment, hold product attributes exactly fixed.

5.5 Labor supply

5.6 Within-city approach using UberBlack

We now consider the effects of changes in the base fare, but using UberBlack as a within-city comparison. As such, the sample for this analysis is restricted to cities in the panel with an UberBlack service. The UberBlack panel was constructed in the same way as the UberX panel, except that the driver mar-

Figure 10: Effects of fare changes on measures of driver week-to-week churn



Notes: This figure plots the weekly base fare indices for UberX and UberBlack services for US cities with both services. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week.

ket level attributes were calculated using only those drivers that drove for UberBlack exclusively in the week in question and were not "cross-dispatched" to UberX trips.

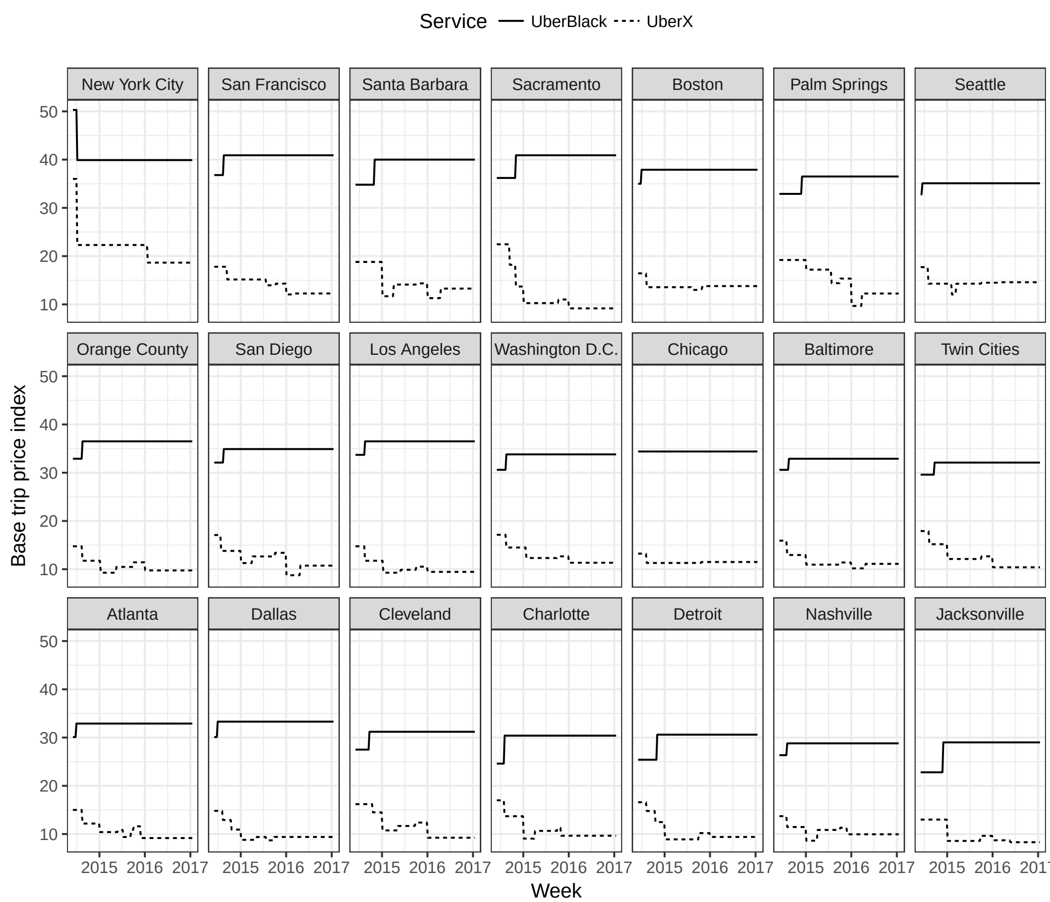
Figure 11 plots the base fare indices for both UberX and UberBlack for the UberBlack panel. The UberBlack price index is indicated by a solid line and the UberX price index is indicated by a dashed line. In all cities, the UberBlack base fare index has been constant since late 2014. During that same period, there has been substantial variation in the UberX base fare in every city in the panel.

For our within-city approach, our key independent variable is now the difference in the price index between UberX and UberBlack in that city. For each city-week, we compute $\Delta \log b_{it} = \log b_{it}^{\text{UBERX}} - \log b_{it}^{\text{UBERBLACK}}$. The outcomes are the analogous differences between UberX and UberBlack in a given city that week. Using these outcomes, we then estimate the regression

$$\Delta y_{it} = \beta \Delta \log b_{it} + \gamma_i + \epsilon_{it}, \tag{5}$$

where γ_i is a city-specific fixed effect. Note that with this within-city design,

Figure 11: UberX and UberBlack base fare indices for the UberBlack panel, by week



Notes: This figure plots the weekly base fare indices for UberX and UberBlack services for US cities with both services. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week.

there is no week-specific effect, as it is removed by differencing.

In terms of interpretation, the coefficients on the independent variable have *approximately* the same interpretation as in our between-city analysis—it is an elasticity of the UberX outcome with respect to the differences in the UberX base fare index. However, we also use the change in UberBlack fares (see Figure 11) as identifying variation, and so a more precise definition of the effect is a percentage change in the difference between the two services—though most of the variation comes solely from changes in the UberX fare, giving the point estimates a similar interpretation to the between-city estimates.[16]

The "long-run" estimates provided by Equation 5 are report in Table 2. Starting in Column (1), a 10% increase in the base fare leads to a 2% decrease in the hourly earnings rate. Note that this point estimate is close to the between-city estimate, though unlike in the between-city comparison from Table 1, the reduction is conventionally significant. As in the between-city analysis, we can decompose the hourly earnings rate into a utilization component and a surge component. In Column (2), we can see that a 10% increase in the base fare lowers utilization by about 11%, which is larger than the between-city estimate. For surge, in Column (3), a 10% increase in the base fare lowers average surge by about 1%, which is the same sign, but small in magnitude relative to the between-city estimate.

As in the between-city analysis, we can explore market adjustment through a richer regression specification. We use the same pre/post-period indicator approach described by Equation 4, adapted for the within-city context. Figure 12 plots the corresponding point estimates for the within-city analysis.

Starting in the leftmost panel, the outcome is the log hourly earnings rate. Following a fare increase, the hourly earnings rate increases almost immediately, with almost full pass-through (i.e., the elasticity is close to 1). However, this effect begins to fall in subsequent weeks. At the end of post-period, the point estimate is close to zero. There is no evidence of a pre-period trend or a level difference.

Turning to utilization in the net panel, we see it declines following a fare increase. By week 15, the point estimate is quite close to the long run estimate of -1. There is no evidence of a pre-period trend or a difference in the pre-period levels.

In the rightmost panel, the outcome is the log surge. We can see that surge declines following a fare increase, but that the post-period shows some

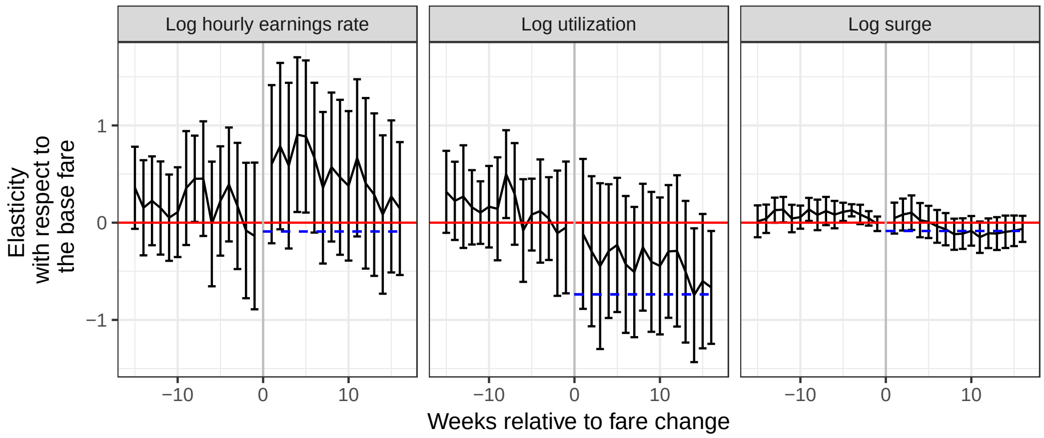
[16]If we exclude pre-2015 data from the panel and thus only rely on UberX variation, the pattern of results is the same, though estimates are less precise, as a non-trivial fraction of UberX fare variation occurred in this pre-period.

Table 2: Within-city estimates of the effects of fare changes on market outcomes using UberX versus UberBlack fare variation

	Dependent variable:		
	log hourly earnings rate	log utilization	log surge
	(1)	(2)	(3)
Diff. in log base fare indices	0.306	-0.335^{**}	-0.143^{***}
	(0.191)	(0.145)	(0.022)
dp:t	0.004	0.002	-0.003^{***}
	(0.003)	(0.003)	(0.0005)
City FE	Y	Y	Y
Observations	2,898	2,898	2,898
R^2	0.478	0.670	0.280
Adjusted R^2	0.470	0.665	0.269

Notes: This table reports OLS regressions of the within-city difference in UberX and UberBlack by week outcomes on the difference in the log base fare index for that week. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The estimating equation is Equation 5. The sample for each regression is the same, and is a city-week panel for a collection of US cities with both UberX and UberBlack. See Section 3.1 for a description of the sample. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week. Fixed effects are included for the city. Standard errors are clustered at the level of the city. Significance indicators: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

Figure 12: Within-city estimates of the effects of fare changes on by-week market outcomes, over time



Notes: This figure plots the effects of changes in the difference in base fare between UberX and UberBlack on the difference in market outcomes for UberX and UberBlack. The estimating equation is based on Equation 4, but using UberBlack within the same city as the comparison. The x-axis are weeks relative to a change in the difference in the relative base fare index. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week. The horizontal dashed blue line indicates the "long-run" effect estimate from Equation 5. 95% CIs are shown for each point estimate and standard errors are clustered at the city level.

evidence of a u-shaped pattern. There is no strong evidence of a pre-period trend, though there is perhaps some evidence of higher levels.

Overall, the within-city approach shows the same basic pattern of results as the between-city analysis. However, the within-city approach indicates little as evidence of targeting, as pre-period estimates are all close to zero, and show no systematic bias. Less welcome, the within-city estimates are less precise.

5.7 Synthetic control approach

Because of the rapid growth of Uber, the panel regression approach works poorly when the outcomes are market quantities. An advantage of a synthetic control approach is the synthetic control only needs to approximate the focal city in a small window around the fare change. Furthermore, we can evaluate how well a synthetic control approximates a focal city on a case-by-case basis, which in turn allows us to remove "bad" comparisons from our analysis.

To begin, for each city in our data, we selected broadly similar cities to serve as the donor pool. We used this first stage screening because we found that including all cities in the donor pool led to over-fitting. To construct a similarity measure for the focal city, we calculated (a) the average difference in the log driver hourly earnings rate over the period relative to every other city and (b) the by-week correlation in the hourly earnings rate. These two measures capture the notion that two cities are not only similar in levels but tend to "move" together, most likely because of similar weather patterns. We combine the two measures by normalizing them and weighting them both equally. From this ordered list, we selected the top 20 cities for each focal city and defined them as the donor pool.

For each fare change in our data, we took the restricted list of donor cities and excluded cities that had fare changes in the 15 weeks before and the 15 weeks after the fare change in the focal city. If the resulting donor pool was empty, we excluded that fare change from the sample. We then ran the synthetic control algorithm described in Abadie et al. (2011), using the driver hourly earnings rate as the primary outcome and surge and utilization as the other covariates, all in logs.

For each fare change for which a synthetic control could be constructed, for each outcome, we computed the by-week difference between the focal city and the synthetic control, using the same synthetic control for all outcomes. We scale by the by-week differences in the size of the fare change (in percentage terms), and so our effect estimates are

$$\beta_{it} = \frac{\left(y_{it}^{T} - y_{it}^{C}\right)}{\Delta b_i / b_i}. \tag{6}$$

This scaling makes all point estimates comparable to the panel estimates.[17]

[17] Our scaling approach is similar to the approach taken in Dube and Zipperer (2015),

5.8 Synthetic control estimates of the effects on fare changes on driver outcomes

Although our intent for using a synthetic control approach is to estimate the effects of fare changes on market quantities, the method can be used for the same outcomes used in our two panel analyses. Recapitulating our panel analysis outcomes is useful, as it allows us to benchmark our synthetic control approach against our more conventional panel results.

For each fare change for which a synthetic control can be constructed, we have an estimate of the effect of that change. However, not all estimates are equally good—for some fare changes, there are wide gaps between the focal city and the synthetic control in the pre-period. As a measure of the goodness of a particular synthetic control, we compute the maximum absolute difference (MAD) in the pre-period. We then use this MAD metric to screen out bad synthetic control estimates.

We use MAD cutoffs of 1, 2, 4 and "Inf" (i.e., the whole sample) and compute the average by-week effects for those estimates that remain. The resulting combined estimates are plotted in Figure 13 for the log hourly earnings rate, log utilization and log surge. The estimate for each MAD cutoff is labeled with the sample size next to the MAD cutoff (expressed a percentage of the full sample).

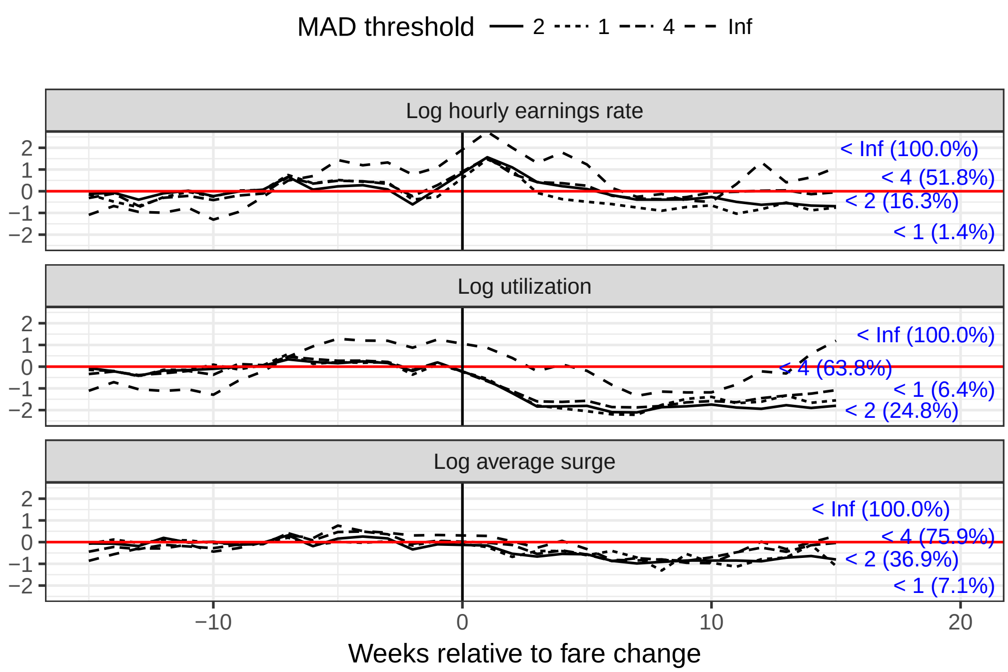
Figure 13 illustrates the importance of screening out poor synthetic controls. For example, in the hourly earnings rate and utilization panels, the no-cutoff "Inf" estimates perform very poorly in the pre-period and give implausible post-period estimates. In contrast, each finite cutoff gives pre-period weekly averages that are quite close to zero in the pre-period and gives post-period results that are qualitatively similar to the panel regression results.

The downside of screening by MAD is a reduced sample size and hence greater variance in the estimate. For example, with a MAD cutoff of 2 for the hourly earnings rate, only 16% of the synthetic control estimates are included.

who combine synthetic control estimates of the effects of minimum wage changes of varying size.

In contrast, that same MAD cutoff applied to utilization allows for nearly a quarter of estimates to be included, and when applied to the surge outcome, about 37% of estimates can be included.

Figure 13: Synthetic control estimates of the effects of fare changes on market quantities, by pre-period match criteria



Notes: This figure plots the average difference between cities experiencing a fare change and a synthetic control city comprising similar cities that contemporaneously did not have a fare change. All synthetic control effects are scaled by the change in the base fare index to make the results comparable to the panel estimates. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week. The different lines represent different selection criteria employed for whether a synthetic control estimate is included in the average: for each line, the cutoff value is shown (which is either Inf, 4, 2 or 1) and next it, the fraction of all fare changes this restriction will include.

To compute a single preferred estimate, we use a two step procedure. First, we choose a MAD cutoff and remove those estimates that are above the cutoff.

Second, we weight the remaining estimates by the inverse of the pre-period mean squared error, putting more weight on our better estimates.

Figure 14 plots the by-week estimated treatment effects for the hourly earnings rate, utilization, and surge as outcomes using the screening and weighting scheme described above. The by-week mean is plotted in black, with a 95% confidence interval placed around the point estimate. The component individual synthetic control estimates are plotted in light gray. By plotting the component fare changes, we can see that there is substantial heterogeneity in outcomes for different cities. From the perspective of any individual driver in any particular city, the central tendency in the data might not be experienced.

In the top panel of Figure 14, the outcome is the log hourly earnings rate. There is a substantial pass-through of a fare increase followed by a gradual decline. The estimated effect eventually turns negative by week 6. In the middle panel, the outcome is the log utilization. Utilization strongly declines following a fare increase and the change appears to be persistent. In the bottom panel, the outcome is the log surge, which declines following a fare increase.

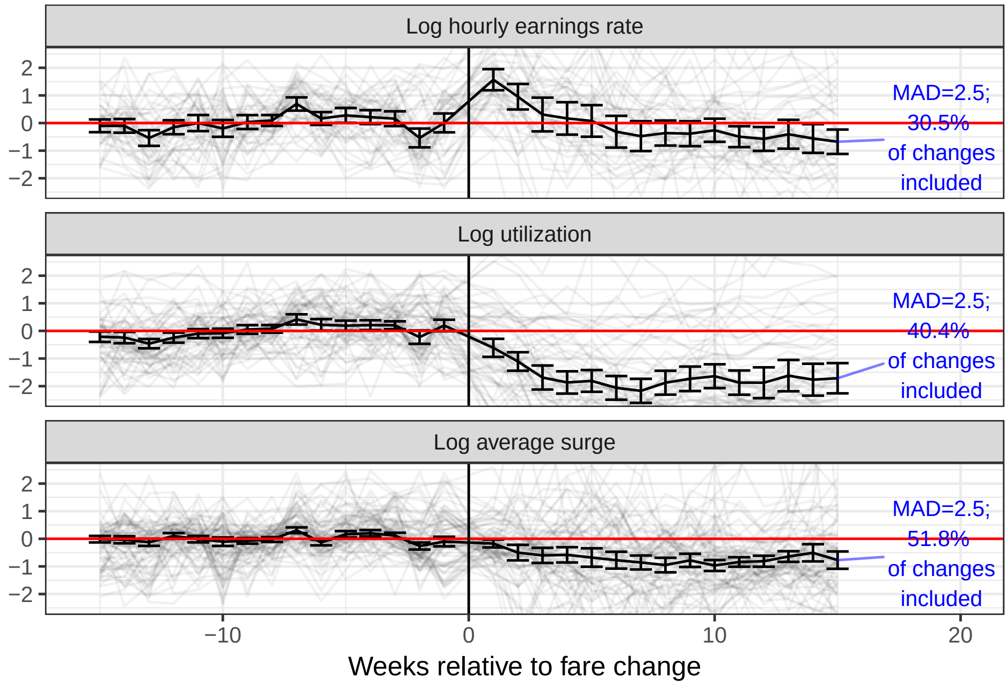
Overall, the synthetic control results are broadly similar to the between-city and within-city approaches, though the point estimates do differ (we will explicitly compare these different estimates in the next section).

5.9 Comparison of driver outcome estimates

We have presented estimates of the effects of fare changes using three different approaches: between-city, within-city, and synthetic control. We plot the by-week point estimates for the three approaches in Figure 15. The samples differ somewhat relative to what was presented earlier. The between-city estimates presented here come from regressions fit only using those cities that comprise the within-city sample. The synthetic control estimates use the pre-period MAD cutoff of 2.5. We do not restrict the data to only UberBlack cities, as the synthetic control estimates are already fairly imprecise.

The general pattern of results seen in in Figure 15 is similar across methods.

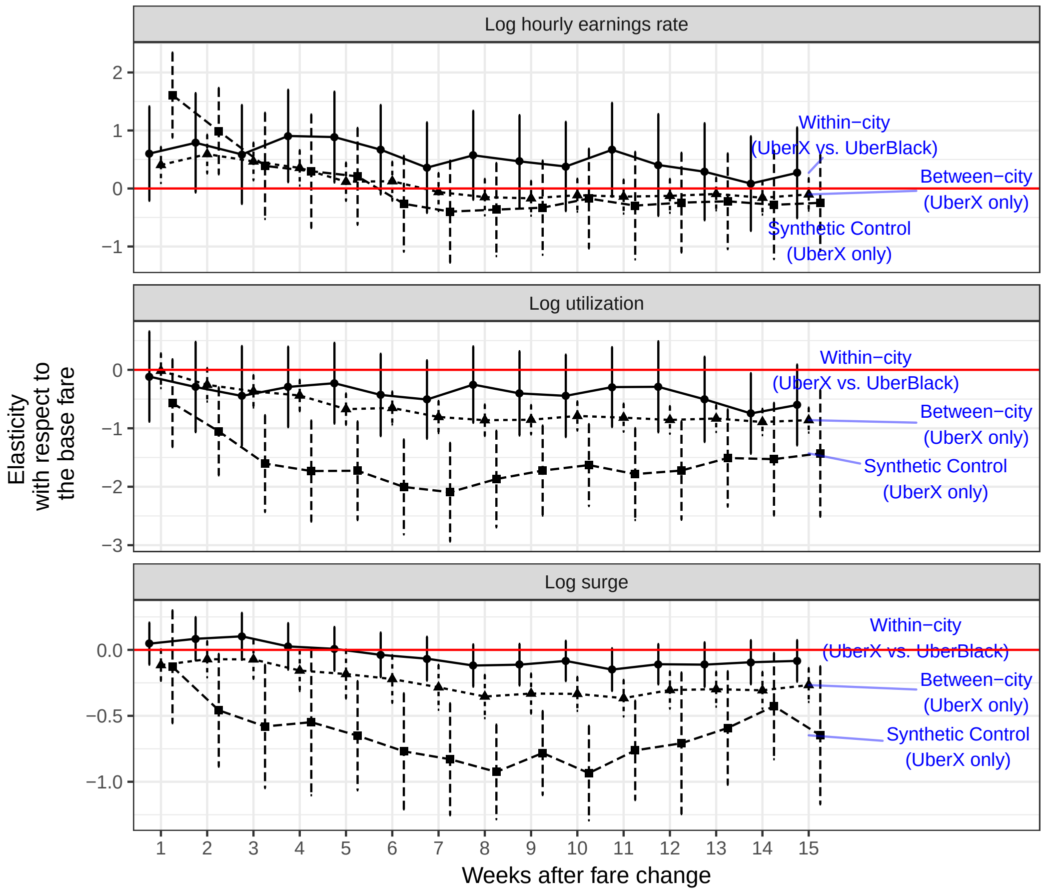
Figure 14: Synthetic control estimates of the effects of fare changes on driver outcomes



Notes: This figure plots the the difference between cities experiencing a fare change and a synthetic control city comprising similar cities that contemporaneously did not have a fare change. Only synthetic control estimates where the maximum absolute pre-period difference between the focal city and synthetic control was less than 2.5 are included. The solid black line indicates the average value, weighted by the pre-period MSE, with error bars indicating a 95% CI. All synthetic control effects are scaled by the change in the base fare index to make the results comparable to the panel estimates. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week.

For the hourly earnings rate, following a fare increase, the hourly earnings rate increases at first, but then declines over time. In the long-run, the effect on the hourly earnings rate is close to zero for all three approaches. In contrast, for all three approaches, we see persistent changes in both utilization and surge following a fare change.

Figure 15: Comparison of the effects of fare changes using different empirical approaches



Notes: This figure shows the by-week estimates of the effects of a fare change on various market outcomes. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week. Three different estimates are shown: the between-city panel estimates, the within-city panel estimates, and the synthetic control estimates, using the 2.5 pre-period cutoff and weighting by the inverse pre-period MSE.

Despite the qualitatively similar pattern, there are substantial differences in magnitudes. For example, the synthetic control estimate for the hourly earnings rate shows a much larger initial pass-through of the fare change. We also see much larger effects for both utilization and surge for the synthetic control estimates compared to the panel estimates.

As our interest is primarily in the long-run effects of fare changes, in Table 3, we report the point estimates at one week after a fare change, for each of our three approaches. Starting in the leftmost column, where the outcome is the driver hourly earnings rate, all the point estimates are close to zero. The most negative (and least precise) is from the synthetic control, which suggests a 10% increase would lower the driver hourly earnings rate by about 2.5%, whereas the within-city estimate suggests a 10% fare increase would raise earnings by about 1.6%. However, none of these estimates are different from zero at conventional significance levels.

Table 3: Comparison of week 15 elasticity estimates with respect to the base fare, by different estimation approaches

Approach	Log hourly earnings rate	Log utilization	Log surge
Between-city	-0.102 [0.14]	-0.86 [0.11]	-0.267 [0.06]
Within-city	0.155 [0.18]	-0.803 [0.17]	-0.239 [0.05]
Synthetic Control	-0.247 [0.42]	-1.429 [0.54]	-0.648 [0.26]

Notes: This table reports the elasticities for various outcomes at week 15 with respect to the base fare index, using three different approaches. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. Three different estimates are shown: the between-city panel estimates (see Section 5.2), the within-city panel estimates (see Section 5.6), and the synthetic control estimates (see Section 5.7), using the 2.5 pre-period cut-off and weighting by the inverse pre-period MSE. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week. See Section 3.1 for a description of the panel.

For utilization, the within-city and between-city point estimates are quite close, with a 10% increase in the base fare lowering utilization by about 8%. In contrast, the (much less precise) synthetic control estimate shows a much larger effect, implying a 10% fare increase would decrease utilization by about

15%. For surge, again, the within-city and between-city point estimates are quite close, with a 10% fare increase reducing the average surge multiplier by about 2.5%, whereas the imprecise synthetic control result implies a 7% decrease in average surge.[18]

5.10 Synthetic control estimates of the effects of fare changes on market quantities

We now turn to the effects of fare changes on market quantities, namely the total driver hours-worked, $S(w)$ in the model, the number of active drivers, and the number of trips, or approximately Q in the model. As in Section 5.8, we explore various synthetic control goodness measures.

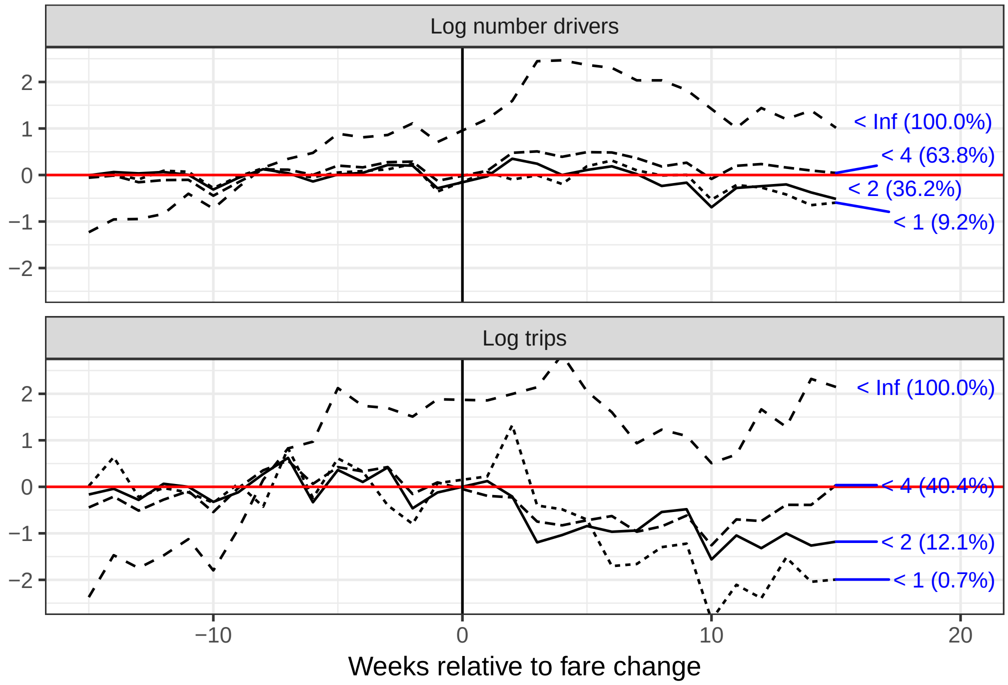
Figure 16 shows the average synthetic control effect estimate using various MAD cutoffs for the pre-period match. For market quantities, it is even more important to screen out bad estimates. The estimates when the MAD cutoff is "Inf" or ∞ exhibit poor match in the pre-period.

The three restricted estimates with a MAD cutoffs of 1, 2 and 4, all give patterns of results that are similar, though there are differences in the point estimates. For example, for the log trips outcome in the bottom panel, the highly restricted sample (MAD < 1) has a final point estimate close to -2, but only includes 0.7% of the sample, which is actually just a single fare change. Consistent with the increased variance that arises from using a single sample, this series shows a jump in the number of trips in the second week following a fare change that is almost certainly a statistical artefact, as it disappears with the larger samples afforded by relaxing the restriction to a MAD cutoff of 2. With a MAD cutoff of 2, the sample increases to about 12% of all fare changes, and with a MAD cutoff of 4, it increases to a bit more than 40% of the sample.

To compute a single preferred estimate, we use the same two step procedure used in Section 5.8 and plot the results in Figure 17. In the top panel, the

[18]It is important to note that with our MAD cutoff approach, the three different outcomes are estimated with different samples, and so we do not expect the nearly accounting-identify decomposition of the driver hourly earnings rate to hold.

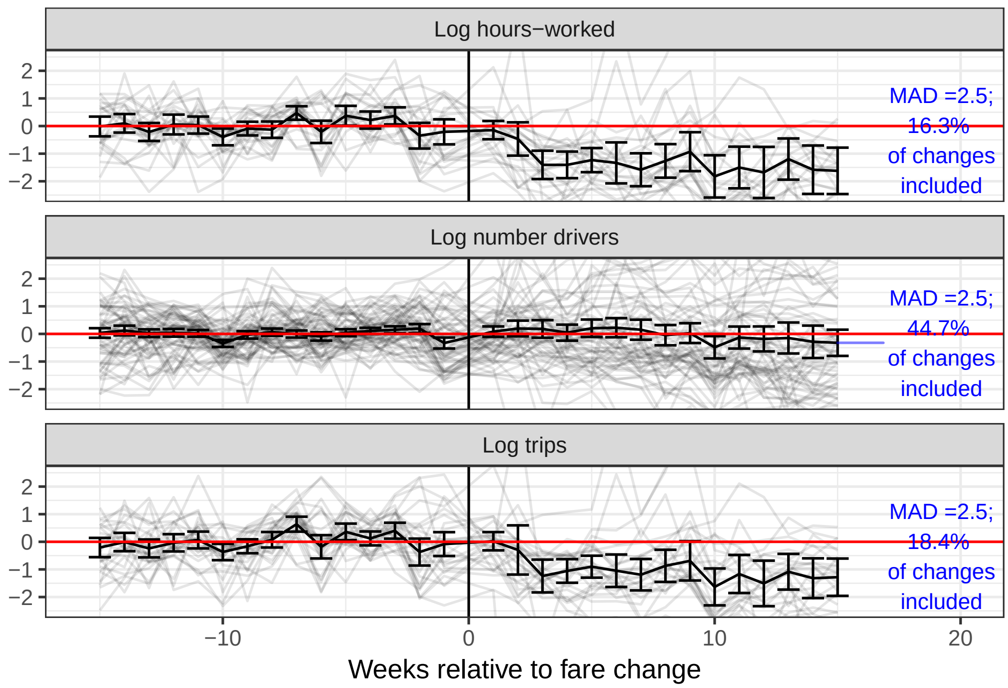
Figure 16: Synthetic control estimates of the effects of fare changes on market quantities, by pre-period match criteria



Notes: This figure plots the average difference between cities experiencing a fare change and a synthetic control city comprised of similar cities that contemporaneously did not have a fare change. The different lines represent different selection criteria employed for whether a synthetic control estimate is included in the average: for each line, the MAD (maximum absolute difference) cutoff value is shown (which is either Inf, 4, 2 or 1) and next it, the fraction of all fare changes this restriction will include. Hours-worked is the total number of hours worked (i.e., had the Uber app on and were available for dispatch or were driving passengers, or enroute to pick up passengers) by drivers in that that city, in that week. The number of drivers is the total number of drivers in that city that worked at least some number of hours.

outcome is the log number of hours-worked. The total number of hours worked declines, with an elasticity close to -1 as early as three weeks after the fare change. Recall that by week 3, from Figure 14, the hourly earnings rate is still slightly positive, though the confidence interval includes zero. In short, we observe a large reduction in hours-worked despite little or no change in the hourly earnings rate. This is consistent with drivers supplying labor highly elastically to Uber.

Figure 17: Synthetic control estimates of the effects of fare changes on market quantities



Notes: This figure plots the difference between cities experiencing a fare change and a synthetic control city comprised of similar cities that contemporaneously did not have a fare change. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. Hours-worked is the total number of hours worked (i.e., had the Uber app on and were available for dispatch or were driving passengers, or enroute to pick up passengers) by drivers in that that city, in that week. The number of drivers is the total number of drivers in that city that worked at least some number of hours. The number of trips is the number of trips completed. Only synthetic control estimates where the maximum absolute pre-period difference between the focal city and synthetic control was less than 2.5 are included. The solid black line indicates the average value, weighted by the inverse pre-period MSE, with error bars indicating a 95% CI.

A change in the number of hours-worked could be due to changes on the extensive or intensive margins. To explore the extensive margin, in the middle panel, the outcome is the log number of drivers active on the platform. There is little evidence that a fare change affects the numbers of drivers, which implicates the intensive margin as the source for the change. One of the adjustment margins discussed in Section 4—a pushing out of the supply curve—was not a factor in explaining how the market adjusted. However, a caveat is that estimates are quite imprecise. The lack of pre-period effects on the number of drivers active implies that Uber cities did not engage in changes in anticipatory on-boarding intensity (e.g., recruiting more drivers before a fare increase).

In the bottom panel, the outcome is the log number of trips taken. We can see that the number of trips declines after a fare increase.[19] We had indirect evidence that this would be the case, given the declines in utilization and hours-worked following a fare increase.

5.11 Market labor supply elasticities

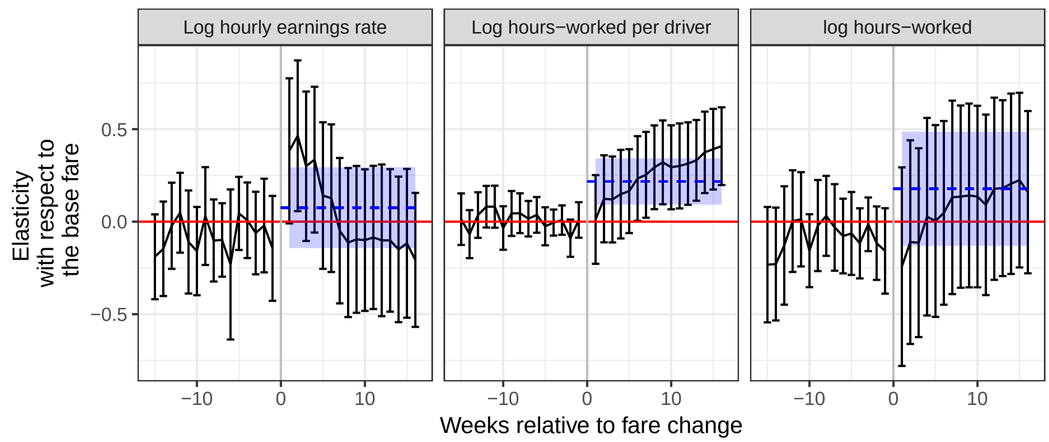
We have characterized the driver labor supply to Uber as not only being highly elastic, but empirically indistinguishable from infinity: in the long-run, we observe large changes in hours-worked, despite no detectable change in the hourly earnings rate. To see this by week, we return to our between-city approach. We compare the hourly earnings rate and the hours-worked week-by-week, Figure 19 plots the effects on both outcomes, side by side.

In the first period after the fare increase, the hourly earnings rate increases by about 40%. That same period, hourly-worked increases by about 20%, implying a 0.5 labor supply elasticity. An important caveat is that both measures are imprecise. This is not an elasticity that applies in later weeks: note that by 15 weeks after the fare change, there is no difference in the observed hourly earnings rate, and yet there is about a 20% reduction in hours-worked, implying an infinite labor supply elasticity.

How do we reconcile infinite elasticity findings with highly credible (and finite) micro estimates from this exact same empirical context—namely Angrist et al. (2017) and Chen et al. (2017)? Part of the reconciliation is that the market labor supply elasticity is not the average of the individual labor supply elasticities of drivers on the platform. As a simple but extreme example, imagine that drivers have idiosyncratic reservation wages, but no intensive margin

[19]Note that for this outcome, there are substantially fewer paths plotted, as relatively few synthetic control estimates could obtain a reasonable match to the focal city in the pre-period.

Figure 18: Effects of fare changes on driver hourly earnings rate, hours per driver, and driver "churn" measures



Notes: This figure plots the effects of changes in the UberX base fare on hourly total earnings (which includes promotional payments) and (2) hours-worked per driver. These effects are from an OLS estimation of Equation 4. The sample is a panel of US cities—see Section 3.1 for a description. The x-axis are weeks relative to a fare change. The independent variable is the base fare index. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. As all outcomes are in logs, the point estimates can be interpreted as elasticities, which are estimated using both fare increases and decreases. The horizontal dashed blue line in the post period indicates the "long-run" effect corresponding to Equation 3. Fixed effects are included for the city and for the week. 95% CIs are shown for each point estimate and standard errors are clustered at the city level.

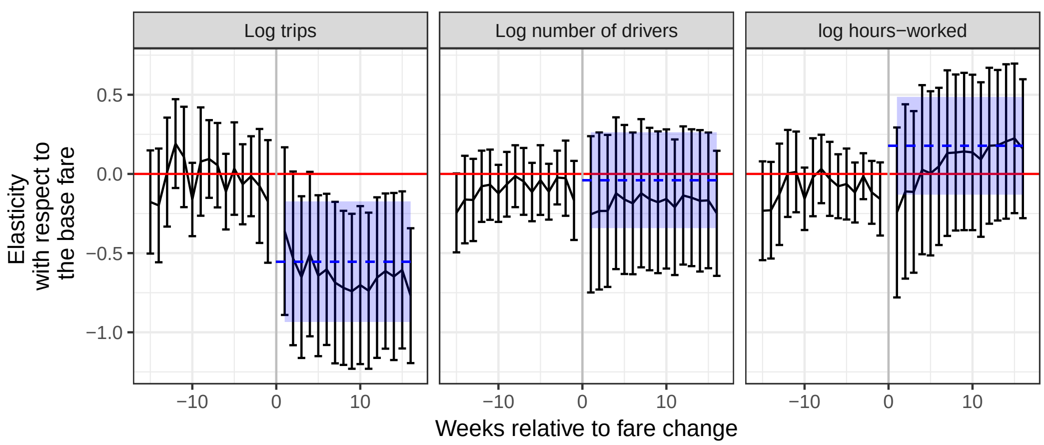
elasticity—they either work or they do not. If there are sufficient numbers of drivers with reservation wages near the market wage, then we might find the market labor supply is highly elastic, even though each inframarginal driver has a labor supply elasticity of zero at the market wage. In short, a group of highly inelastic workers at the going market wage can create a highly elastic market labor supply.

In the Uber context, it seems quite likely that the region around the market wage is indeed "thick" with workers near their reservation wage, given the existence of competitor platforms. As such, both platforms would have lots of bunching of individual reservation wages near the market wage.

This market-versus-individual elasticity distinction is important when comparing our results to Chen et al. (2017). A driver could be highly elastic with respect to the platform, but still evince "micro" behaviors consistent with a finite elasticity. Suppose there exists a competitor ride-sharing platform that offers exactly the same average hourly earnings rate and the same temporal pattern of variation in that rate. Would-be drivers could be indifferent between the two platforms—suppose there is an ϵ of switching cost. Drivers would still decide when to work, weighing off changes in their outside option to the current platform hourly earnings rate. They would obtain a surplus because of this ability to pick and choose and would exhibit a "reasonable" Frisch labor supply elasticity.

Now, suppose that the alternative platform could offer hourly earnings rates $w + \Delta w$, with $\Delta w > \epsilon$, no matter how many drivers switched. All drivers would switch, and we would observe an effectively infinite labor supply elasticity *to the platform* even though on the new platform, they go back to working in a manner consistent with a finite Frisch labor supply elasticity.

Figure 19: Effects of fare changes on driver hourly earnings rate, hours per driver, and driver "churn" measures



Notes:

6 Discussion and conclusion

The key finding of the paper is that following a fare change, ride-sharing markets adjust primarily through changes in driver utilization. There is no detectable long-run effect on the driver hourly earnings rate, with a "long-run" being about 8 weeks. This is consistent with drivers supplying labor highly elastically to Uber. Simply comparing the main time series, we can see that despite large reductions in fares, there has been no detectable trend in average hourly earnings rate. Interestingly, this lack of price effects *on average* seems to apply even to the introduction of Uber into US cities—Berger et al. (2017) presents evidence that the introduction of Uber lowered the average hourly earnings of professional drivers, but as Angrist et al. (2017) point out, the increase in earnings from self-employed drivers left the average unchanged.

In our empirical analysis, we assumed that Uber was changing fares without conditioning on market-specific attributes. When ride-sharing markets were less mature and there was less practical experience in managing these markets, assuming Uber would change fares as-if at random is plausible. With hindsight about how the market seems to adjust, Uber might make different choices—namely by picking a preferred fare/utilization equilibrium.

From any particular market starting point, at a higher fare, there are fewer rides taken, but revenue per ride is higher (assuming a fixed commission). Revenue is higher both for the simple reason that the fare is higher, but also because Uber can meet the lower level of demand with fewer hours driven, which, if Uber faced an upward sloping labor supply curve, means those hours would earn a lower hourly rate. This second aspect to the problem—the affect of the fare on labor costs—appears to be moot, as we find that Uber seems to instead face a horizontal labor supply curve. As such, it has no incentive to distort the quantity of rides to be lower, as it would with an upward sloping labor supply curve.

With a higher driver utilization, each hour of work is more productive, allowing Uber to meet the same amount of passenger demand with fewer drivers. Although utilization is, as we show, sensitive to the fare, many of

Uber's platform improvements can interpreted as attempts to raise utilization though technological means, such as "forward dispatch" (matching drivers before their current trip is finished based on predicted drop-off time and location) and having passengers re-locate slightly before pick-up. With the move to up-front pricing, Uber could potetially charge more for utilization-reducing trips, such as those to areas where a return trip with a paying passenger is unlikely.

To the extent we think of Uber's fare selection problem as applying a markup rule to its unit costs, technological improvements in utilization would lower those unit costs, implying that the optimal fare adjustment has typically been a fare reduction. This line of argument provides an intriguing as-if explanation for why Uber has continually reduced the base fare over time. It would also explain why, if anything, the hourly earnings rate rose following fare cuts—if Uber was cutting fares because a higher utilization was obtainable, the pre-cut fare was unprofitably in the elastic region of the demand curve (recall Proposition 1, which signed the effects of fare changes on the driver hourly earnings rate in terms of the position on the demand curve).

This paper has focused on market-level attributes and outcomes. A natural direction for future work would be to take an individual driver perspective. In particular, it would be interesting to consider driver micro labor supply decisions, focusing on the role of the individual differences in costs. It seems probable that drivers vary in their preferences over the different utilization equilibria, both because of their personal preferences about being "busy" as well as their capital, with drivers with less fuel efficient vehicles preferring the low utilization equilibrium.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller, "Synth: An R package for synthetic control methods in comparative case studies," *Journal of Statistical Software*, 2011, *42* (i13).

Abraham, Katharine G, John Haltiwanger, Kristin Sandusky, and James R Spletzer, "Measuring the gig economy: current knowledge and open issues," in "IZA Labor Statistics Workshop Changing Structure of Work" 2017.

Akerlof, George A, "Gift exchange and efficiency-wage theory: Four views," *The American Economic Review*, 1984, *74* (2), 79–83.

Angrist, Joshua D., Sydnee Caldwell, and Jonathan V. Hall, "Uber vs. Taxi: A driver's eye view," *Working Paper*, 2017.

Arnott, Richard, "Taxi travel should be subsidized," *Journal of Urban Economics*, 11 1996, *40* (3), 316–333.

Autor, David H, "Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing," *Journal of Labor Economics*, 2003, *21* (1), 1–42.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul, "Social incentives in the workplace," *The Review of Economic Studies*, 2010, *77* (2), 417–458.

Berger, Thor, Chinchih Chen, and Carl Benedikt Frey, "Drivers of disruption? Estimating the Uber effect," *Working paper*, 2017.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How much should we trust differences-in-differences estimates?," *The Quarterly Journal of Economics*, 2004, *119* (1), 249–275.

Borusyak, Kirill and Xavier Jaravel, "Revisiting event study designs," *Working Paper*, 2016.

Cairns, Robert D. and Catherine Liston-Heyes, "Competition and regulation in the taxi industry," *Journal of Public Economics*, 01 1996, *59* (1), 1–15.

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler, "Labor supply of New York City cabdrivers: One day at a time," *The Quarterly Journal of Economics*, 1997, *112* (2), 407–441.

Castillo, Juan Camilo, Daniel T. Knoepfle, and E. Glen Weyl, "Surge pricing solves the wild goose chase," *Working Paper*, 2017.

Chen, M. Keith and Michael Sheldon, "Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform," *Working paper*, 2015.

_ , Judith A. Chevalier, Peter E. Rossi, and Emily Oehlsen, "The value of flexible work: Evidence from Uber drivers," *Working Paper*, 2017.

Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe, "Using big data to estimate consumer surplus: The case of Uber," *Working Paper*, 2016.

Dube, Arindrajit and Ben Zipperer, "Pooling multiple case studies using synthetic controls: An application to minimum wage policies," *Working Paper*, 2015.

Edlin, Aaron S and Pinar Karaca-Mandic, "The accident externality from driving," *Journal of Political Economy*, 2006, *114* (5), 931–955.

Farber, Henry S., "Is tomorrow another day? The labor supply of New York City cabdrivers," *The Journal of Political Economy*, 2005, *113* (1), 46–82.

_ , "Reference-dependent preferences and labor supply: The case of New York City taxi drivers," *American Economic Review*, 06 2008, *98* (3), 1069–1082.

_ , "Why you can't find a taxi in the rain and other labor supply lessons from cab drivers," *The Quarterly Journal of Economics*, 11 2015, *130* (4), 1975.

Filippas, Apostolos, Srikanth Jagabathula, and Arun Sundararajan, "Exit, voice, and availability: A randomized field experiment on sharing economy marketplace design.," *Working Paper*, 2018.

Frechette, Guillaume, Alessandro Lizzeri, and Tobias Salz, "Frictions in a competitive, regulated market: Evidence from taxis," *Working Paper*, 2015.

Friedman, Jerome, Trevor Hastie, and Rob Tibshirani, "glmnet: Lasso and elastic-net regularized generalized linear models," *R package version*, 2009, *1* (4).

Hall, Jonathan V and Alan B Krueger, "An analysis of the labor market for Uber's driver-partners in the United States," *Industrial and Labor Relations Review*, Forthcoming.

_ , Cory Kendrick, and Chris Nosko, "The effects of Uber's surge pricing: A case study," *Working Paper*, 2016.

Hsieh, Chang-Tai and Enrico Moretti, "Can free entry be inefficient? Fixed commissions and social waste in the real estate industry," *Journal of Political Economy*, October 2003, *111* (5), 1076–1122.

Jackson, Emilie, Adam Looney, and Shanthi Ramnath, "The Rise of Alternative Work Arrangements: Evidence and Implications for Tax Filing and Benefit Coverage," *Office of Tax Analysis Working Paper*, 2017, *114.*

Katz, Lawrence F and Alan B Krueger, "The rise and nature of alternative work arrangements in the United States, 1995-2015," *Working Paper*, 2016.

Kuhn, Peter, "Is monopsony the right way to model labor markets? A review of Alan Manning's 'Monopsony in Motion'," *International Journal of the Economics of Business*, 2004, *11* (3), 369–378.

Lazear, Edward P, "Performance pay and productivity," *American Economic Review*, 2000, *90* (5), 1346–1361.

Mankiw, N Gregory and Michael D Whinston, "Free entry and social inefficiency," *The RAND Journal of Economics*, 1986, *17* (1), 48–58.

Manning, Alan, *Monopsony in motion: Imperfect competition in labor markets*, Princeton University Press, 2003.

Mas, Alexandre and Amanda Pallais, "Valuing alternative work arrangements," *American Economic Review*, 2017, *107* (12), 3722–59.

_ **and Enrico Moretti**, "Peers at work," *The American economic review*, 2009, *99* (1), 112–145.

Mortensen, Dale T and Christopher A Pissarides, "New developments in models of search in the labor market," *Handbook of labor economics*, 1999, *3*, 2567–2627.

Parry, Ian WH, Margaret Walls, and Winston Harrington, "Automobile externalities and policies," *Journal of Economic Literature*, 2007, *45* (2), 373–399.

Rosen, Sherwin, "Short-run employment variation on class-I railroads in the US, 1947-1963," *Econometrica: Journal of the Econometric Society*, 1968, pp. 511–529.

Tibshirani, Robert, "Regression shrinkage and selection via the lasso," *Journal of the Royal Statistical Society. Series B (Methodological)*, 1996, pp. 267–288.

A Online Appendix: Simulating Uber fare change decision-making

Our between-city identifying assumption is that, conditional upon observables, fare changed are exogenous. Although we find that pre-period indicators are typically close to zero and show no trend, there is still a natural concern that

Uber is selecting on factors for a fare change that do not show up in the pre-trend but are still forward-looking.

As a robustness check, we perform the following placebo test: (1) we model Uber's fare change decision and magnitude, (2) generate simulated fare changes for our collection of cities and weeks, (2) generate the implied fares from these simulations and (2) estimate our regression model with the same outcomes, but using the simulated fare.

One concern this this approach is that the model predicting which cities get a fare change can't be "too good" in the sense that it cannot just predict the realized draw. This would occur, if, for example, we used a full saturated model with city and week effects, or more generally with a model that was overfit. In a nutshell, we want to approximate the decision rule Uber would have used (and a over-fitt model would not be a good approximation). To avoid this possibility, do not include indicator interactions but instead use a generalized linear model with at-the-moment city-specific attributes and use regularization to eliminate over-fitting (Tibshirani, 1996; Friedman et al., 2009). We fit two models—one to predict a fare increase and another to predict a fare decrease.

If Figure 20 we plot the local linear regression estimates of the fare change mean and standard deviation (in log points), by week.

For the magnitude of the fare changes, if we draw a fare cut, we sample from a truncated normal to the right at 0, and vice versa for a fare increase. If we happen to draw a fare increase and decrease, we simply sample from the untruncated normal.

Figure 21

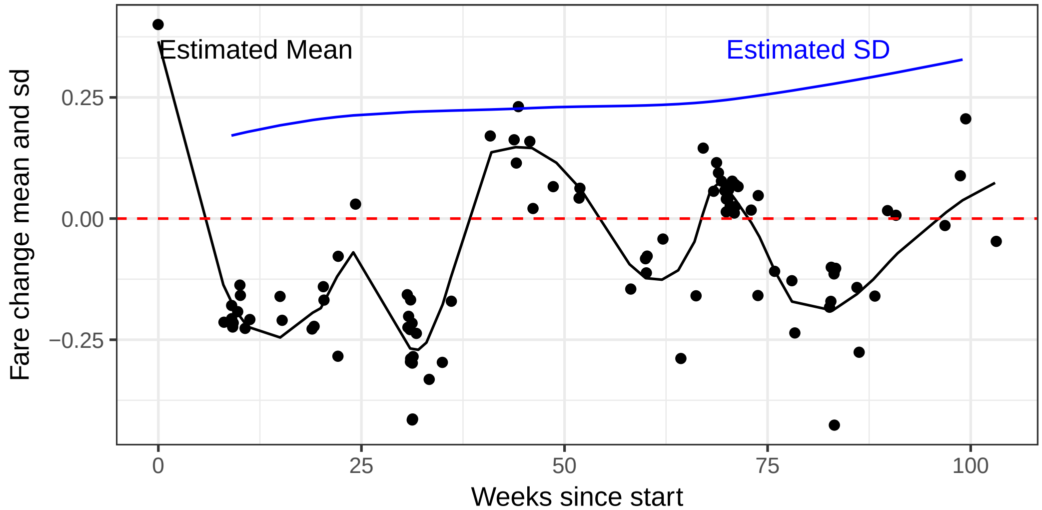
B Multihoming

Drivers can and do drive more multiple platforms.

Some factors discourage it: have to go through on-boarding. Typically need to have two phones. There are non-linear incentives.

The relative market shares are such that fairly small fraction are likely doing it.

Figure 20: All fare changes (in log points) since the start of the panel



Notes: This figure plots the

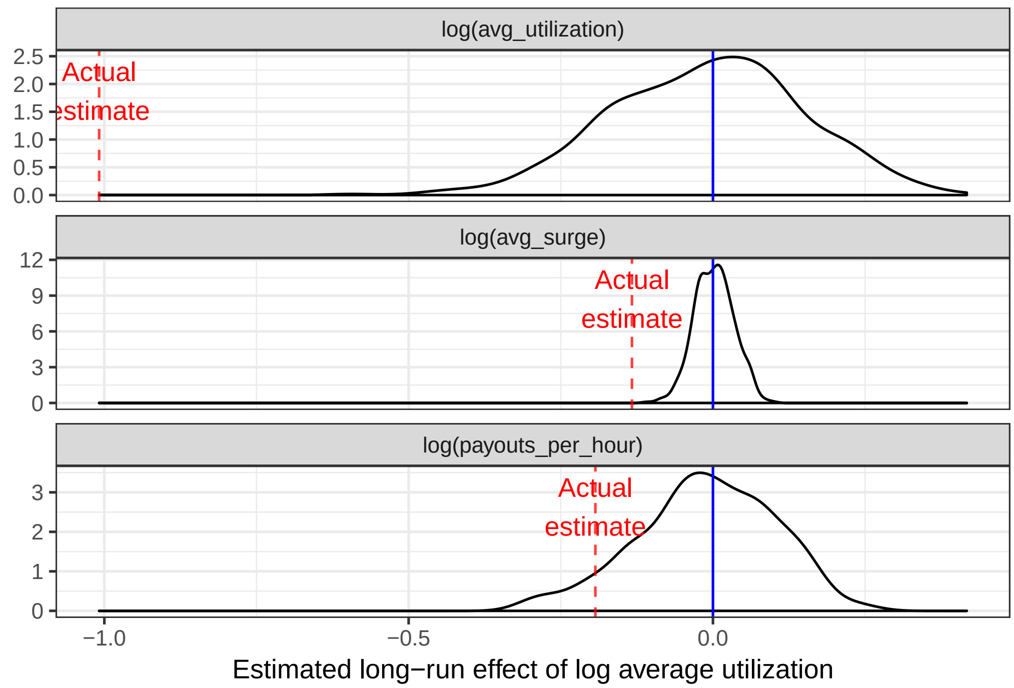
C Lyft

C.1 Competition by city

It is beyond the scope of this analysis to try to model the competition between ride-sharing platforms and the larger for-hire industry. However, we can at least assess whether our panel results are sensitive to the presence of a substantial ride-sharing competitor. To do this, we interact our base price index with Lyft's estimated share of the ride-sharing market. Our estimates of Lyft's market share come from the market research company "Second Measure," which in turn uses credit card data. The reported measures are from each July, from 2014 to 2017. From these measures, we impute weekly measures matching our panel. For cities in which Lyft was not operating that week, we include 0 as their market share.

In Table 4 we report our long-run regressions, mirroring our analysis in Table 1. However, we first use the imputed Lyft share as an outcome variable in Column (1). The coefficient is positive, large in magnitude but insignificant. To the extent we think Lyft benefitted from increased Uber fares, then then

Figure 21: Comparison of actual long-run estimates to bootstrapped estimates with simulated fare changes



Notes:

this is the "right" sign.

In the next columns, we report estimates for the hourly earnings rate, utilization and average surge. Columns (2), (4) and (6) are reproduced from Table 1. In Column (3), (5) and (7), the same outcomes are used, but the base trip price index is interacted with the imputed Lyft market share in that city that week. In every case, we can see that the point estimate on the price index is nearly unchanged with the inclusion of the Lyft share, and that the Lyft share interaction term is close to zero.

The results suggest that the presence of absence of Lyft had no disceible effect on how Uber's marketplace adjusted following fare changes.

Table 4: Effects of fare changes on market outcomes from a city-week panel of UberX markets

	Dependent variable:						
	Lyft share	Hourly earnings		Utilization		Surge	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log base fare index	3.727	-0.092	-0.151	-0.827^{***}	-0.857^{***}	-0.218^{***}	-0.232^{***}
	(2.836)	(0.083)	(0.098)	(0.088)	(0.102)	(0.025)	(0.029)
Lyft share			-0.025		-0.016		-0.006^{*}
			(0.018)		(0.015)		(0.003)
Lyft share × Log base fare index			0.010		0.006		0.002^{*}
			(0.008)		(0.006)		(0.001)
City FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Observations	5,852	5,852	5,852	5,852	5,852	5,852	5,852
R^2	0.907	0.663	0.667	0.732	0.734	0.432	0.434
Adjusted R^2	0.904	0.652	0.656	0.724	0.726	0.414	0.416

Notes: This table reports OLS regressions of city-week outcomes on the log base fare index. The estimating equation is Equation 3. The base fare index is the price to passengers of an un-surged, 6 mile, 16 minute trip in that city, in that week. The sample for each regression is the same, and is a city-week panel of UberX markets. See Section 3.1 for a description of the sample. The hourly earnings rate is the total earnings by drivers (excluding costs and Uber's commission but not including any promotional payments) divided by total hours-worked, for drivers in that city, that week. Utilization is the total hours spent transporting passengers by drivers divided by the total number of hours-worked. Surge is the average value of the multiplier for all trips conducted in that city, during that week. Fixed effects are included for the city and for the week. Standard errors are clustered at the level of the city. Significance indicators: $p \leq 0.10 : \dagger$, $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.