Consumption Insurance and Multiple Jobs: Evidence from Rideshare Drivers

[Job Market Paper. Link to Latest Version]

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Abstract

Emerging rideshare jobs promise workers more choice over their hours. Does this increased flexibility help workers smooth income shocks? A sample of approximately 18,000 rideshare drivers is analyzed from a large, online personal financial service containing information on rideshare income, outside income, spending, and liquid assets. Debt and high credit card utilization are key predictors of participation in ridesharing. In the period after starting ridesharing, rideshare income replaces 73 percent of income losses from main payroll jobs. Sensitivity of spending to main income falls by 82 percent, suggesting substantial increases in consumption smoothing. Matching these empirical findings to a structural intertemporal labor supply model with credit and labor frictions implies benefits from flexible second jobs of over $1,800 per year. The results suggest the value of leisure is relatively low for this group of workers, which has important implications for understanding the welfare costs of income fluctuations.

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1 Introduction

Since pioneering work of Friedman (1957) on household consumption, the literature has explored factors that hamper optimal adjustment to economic shocks, including credit market imperfections, adjustment costs of assets and consumption commitments (Zeldes, 1989; Chetty and Szeidl, 2007; Kaplan and Violante, 2014). Adjusting hours is another consumption-smoothing mechanism (Card, 1994; Low, 2005; Swanson, 2012; Heathcote, Storesletten and Violante, 2014; Blundell, Pistaferri and Saporta-Eksten, 2016), but it can be difficult to adjust hours due to frictions. For example, many workers face employer-determined scheduling. Exploiting the sudden rise of the rideshare industry noted for its hours flexibility, this paper considers how reducing frictions on hours can affect households’ ability to smooth consumption in response to income shocks.

The main objective of this paper is to estimate causal impacts of reducing labor supply frictions on consumption and labor supply. To this end, I exploit a natural experiment that altered flexibility in work arrangements and reduced search and transaction costs. Specifically, recent technological change has allowed more tasks to be performed outside of traditional, arms-length employment relationships. I focus on one notable example: the rideshare industry.\(^1\) Rideshare platforms entered different geographic markets in a staggered fashion beginning in 2012. Figure\(^2\) shows the overall rise in rideshare employment over the period 2012-2016. Strikingly, the number of active rideshare drivers now exceeds taxi drivers and chauffeurs in the U.S.\(^2\)

Why has rideshare employment been so popular? One reason may be that households were constrained in their hours choices before rideshare entry. I begin by sketching a consumption model with endogenous labor supply, credit constraints and frictions on adjusting hours. Households in the model are risk-averse and value leisure. In the steady state, the household is on its labor supply curve, but earnings can vary every pay period in response to

\(^1\)The industry is popularly known by the names of the two major platforms, Uber and Lyft.
\(^2\)On taxi and chauffeur employment, Appendix A1 shows that rideshare drivers are not captured in U.S. survey data.
the employer’s demand. During times of weak demand, households are free to take on second jobs in a spot market, but must pay a fixed cost. I model the introduction of ridesharing as an exogenous fall in this cost.

The model has intuitive predictions: selection into second jobs is decreasing in assets and the fixed cost of taking a second job. After the cost of taking a second job falls, consumption smoothing increases, as households are able to better adjust to shocks using a second job. Consumption increases and steady-state assets fall as households maintain a smaller buffer stock of savings. One natural prediction is that adding a second job helps insure against negative shocks only—households will not work in a second job in response to positive shocks.

I next take the model’s predictions to the data. This paper relies on “big data” from over 1.5 million households from a large personal financial management aggregator for smartphones and computers. In the data, I am able to identify approximately 18,000 ever-rideshare drivers between December 2012 to November 2016, which lines up with the largest rise in rideshare employment. This sample is approximately 1 percent of ever-rideshare drivers over this period.

A key feature of these data is that both outside spending and non-rideshare income are observed. This is a crucial advantage over other research on rideshare labor supply using proprietary company data because most rideshare drivers are working temporarily while between jobs or as a second job. As a result, these studies do not observe the primary source of other income, a severe limitation for understanding household labor supply. Having access to total spending and income allows me to identify high-frequency payroll shocks that induce workers to participate in ridesharing. The size of payroll volatility is large and survey evidence suggests that households have trouble smoothing these shocks.

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3 These data have been previously used in Gelman (2016); Gelman et al. (2014, 2016, 2015) and are similar to but distinct from the data used in Baker (forthcoming) and Ganong and Noel (2017).

4 For instance, Chen et al. (2017)’s identification strategy does not consider changes in reservation wages over time induced by changes in outside income, which I will show to be a very important determinant of rideshare labor supply.

5 These shocks are highly volatile with “fat” tails, consistent with Guvenen et al. (2016). Using high-
Following Blundell, Pistaferri and Preston (2008), I consider a key summary measure of household “insurance”: the elasticity of consumption spending to income. I estimate the elasticity of consumption to payroll income to be approximately 1/3 over the entire sample of workers. To examine the consumption smoothing benefits of rideshare work, I consider how this measure of partial insurance changes around starting rideshare. My research design addresses two main endogeneity issues. First, since movements in main income may be endogenous to movements in consumption, I instrument individual income with income fluctuations common to all coworkers of a given individual at his or her primary job, which should pick up income variation due to changes in firm demand. Second, even though rideshare entry is exogenous, the decision of exactly when to drive for rideshare is still endogenous. This decision is dealt with using a second instrumental variable exploiting cross-city variation in Uber’s launch.

The main findings are as follows: Compared to coworkers at their firms, rideshare drivers have a very similar income process and responsiveness of spending to payroll income before they start rideshare. However, rideshare drivers tend to have lower income and much higher debt and credit utilization, suggesting they are more likely to be borrowing constrained. After a household begins ridesharing, total spending (net of auto expenses) rises by about 3-5 percent and the excess sensitivity of spending to main payroll income falls by over 80 percent in my IV specification. Focusing on the differential response of spending to negative income deviations, which is a key prediction of the model, shows that all of the gain in consumption smoothing comes from the response to negative shocks, with no changes in the response to positive shocks.

I next consider how much households would be willing to pay for access to flexible jobs. I frequency data similar to this paper, Farrell and Greig (2016) find a typical monthly swing in income around $500, half of which comes from payroll income. Monthly swings in income of $500 are not trivial, especially considering that 46 percent of households report being unable to smooth a $400 shock with cash on hand (Board of Governors of the Federal Reserve System, 2017).

A similar research design has also been used to study transportation demand (Hall, Palsson and Price, 2016), motor-vehicle fatalities (Dills and Mulholland, 2017), Brazil and Kirk, 2016, and the effect of Uber on the taxi industry (Berger, Chen and Frey, 2017).
calibrate and estimate via Simulated Method of Moments (SMM) a structural intertemporal labor supply model with credit constraints and hours frictions. My structural estimates imply fixed costs of adjusting hours of over $500 per pay period. This cost cannot be directly mapped to a measure of welfare losses, however, because in many cases households would simply choose not to participate in second jobs. Willingness to pay can be calculated from a consumption equivalence variation exercise similar to Lucas (2003), determining the amount of consumption that would make a household indifferent between costly hours adjustment and flexible jobs. Aggregating over the distribution of shocks and the asset distribution in the pre-period implies households would be willing to pay on average around $1,800 per year for flexible labor supply. To put this number in perspective, willingness to pay for flexible labor supply is about two-thirds of the value from completely eliminating borrowing constraints and has similar welfare implications as eliminating the bottom 25 percent of negative income shocks. These results suggest that income fluctuations can be quite costly in the presence of credit constraints and hours frictions.

The paper proceeds as follows: I briefly discuss related literature in the next subsection. Section 2 sets the stage with an illustrative intertemporal labor supply model with credit constraints, hours uncertainty, and frictional labor supply adjustment. The model’s predictions are next taken to the data. Section 3 provides a detailed discussion of data used in this paper, as well as the construction of the estimation sample and a control group of matched coworkers. In Section 4, I discuss the main research design, results of which appear in Section 5. Structural estimation is performed in Section 6. Section 7 concludes with a summary and discussion of policy implications.

1.1 Related Literature

Much of the consumption smoothing literature tends to be either focused on lifecycle dynamics (e.g. Bodie, Merton and Samuelson 1992, Blundell, Meghir and Neves 1993, Low 2005, Gourinchas and Parker 2002, Heathcote, Storesletten and Violante 2014) and/or a
handful of income events that are easy to identify in existing survey data, such as wage changes (Pistaferri 2003; Heathcote, Storesletten and Violante 2014; Blundell, Pistaferri and Preston 2008; Blundell, Pistaferri and Saporta-Eksten 2016), tax rebates (Johnson, Parker and Souleles 2006; Kaplan and Violante 2014), or unemployment (e.g. Ganong and Noel 2017; Gruber 1997; Card, Chetty and Weber 2007). These events tend to be low-frequency and may or may not be expected. One view of these income fluctuations is that they are not very costly because households have a high value of leisure time (Hagedorn and Manovskii 2008), households have important complementarities between consumption and leisure (Aguiar and Hurst 2005, 2007, 2013), or households can adjust on other margins, such as by varying shopping intensity (Coibion, Gorodnichenko and Hong 2015). An alternative and not mutually exclusive view is that considerable frictions prevent optimal adjustment.

A large body of work in macroeconomics and finance has focused on the implications of credit market imperfections, starting from seminal work by Zeldes (1989), Deaton (1991), and Aiyagari (1994). Kaplan and Violante (2014) argue that rational households will want to invest some of their portfolio in frictional, high-return assets, generating excess sensitivity to transitory shocks.

Few studies have investigated the costs of high-frequency income fluctuations, mainly due to reasons of data availability. In many empirical treatments, an identifying assumption for transitory shocks is that they have no impact on contemporaneous consumption spending (e.g. Blundell, Pistaferri and Saporta-Eksten 2016). On the other hand, financial diaries collected by Morduch and Schneider (2017) document households struggling with paycheck volatility, both predictable (lower demand at work during a local college football game) and unpredictable (checks not arriving on time), by cutting food and decreasing other spending. For the sample of rideshare drivers considered in this paper, revealed preference suggests that high-frequency shocks have at least some costs. If high-frequency volatility were costless, we would not see households take up rideshare employment once it becomes available.

This paper views rideshare employment from the perspective of the key workhorse model
in labor economics, where households also smooth shocks by adjusting labor supply (MaCurdy 1981; Card 1994; Altonji 1993). In a series of recent papers, Swanson (2012, 2014, 2015) provides a general treatment of endogenous labor supply in dynamic consumption models, showing that labor supply has important implications for risk aversion and asset pricing. Heathcote, Storesletten and Violante (2014) find that about 20 percent of shocks over the lifecycle are smoothed by adjusting labor supply. When credit market frictions are added to this class of models, a key result is that they will lead to more volatile consumption, but consumption volatility will be mitigated by an increase in hours worked (Domeij and Floden 2006).

In the standard version of this model, households choose labor supply freely. In reality, households often do not have control over their hours in their main jobs, particularly in high-frequency. Literature examining optimal adjustment in practice has mainly focused on either dual earning households or unemployment search intensity. Research on the “added worker effect” goes back to Mincer (1962), and has most recently been advanced by Blundell, Pistaferri and Saporta-Eksten (2016), who take advantage of the new consumption modules in the PSID. Mankart and Oikonomou (2017) consider dual earners in a search and matching model of the labor market. Card, Chetty and Weber (2007) examine the effect of cash on hand on job search intensity. An earlier literature focused on participation frictions. Cogan (1981) investigates the effect of extensive margin frictions in a static setting. Card (1990) considers a minimum hours threshold of work, the idea being that a portion of the budget constraint is simply unobtainable. Early empirical work focused on testing for the existence of hours constraints (Ham 1986; Altonji and Paxson 1992; Paxson and Sicherman 1996). Taking on a second job, also called “moonlighting” or “multi-job holding” (Shishko and Rostker 1976; Krishnan 1990; Paxson and Sicherman 1996; Zhao 2015), has been viewed as evidence for hours constraints in main jobs.

An alternative hypothesis is that households value task heterogeneity (Renna and Oaxaca 2006). While this may be true for some second jobs, this is unlikely to be the driving force behind becoming a rideshare driver.

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7 In practice, second jobs will face search...
and other costs of work, just as in any first job. I will show that while some rideshare drivers experience an unemployment event, most are adding ridesharing as a second job. One interpretation consistent with this literature is that these households are mitigating hours frictions in their main job.

This paper is also related to a recent literature investigating whether workers value flexibility in their work arrangements. Using experimental variation in schedules offered to call center workers, Mas and Pallais (forthcoming) find that jobseekers are not willing to pay for added flexibility in their employment contracts but are willing to pay substantially to avoid evening and weekend work. Looking at Uber drivers, Chen et al. (2017) use variation in household reservation wages at different times of the day and days of the week to calculate a willingness to pay for flexible work. They find that households would be willing to pay about $150 per week for the flexibility an Uber job provides, mainly because the household can increase hours on evenings and weekends. The model in this paper provides some insight on this contradiction: risk-averse households want stable first jobs, but value flexible second jobs that can be used to mitigate negative shocks in the main job.

This paper differs from earlier work in its focus on multijob holding, which has proven harder to capture in survey data, and by exploiting a source of experimental variation in the availability of flexible second jobs. In addition, I provide insight on consumption smoothing in high-frequency, and on time-series properties of biweekly income processes.

2 Consumption Model with Frictional Second Jobs

This section outlines an illustrative intertemporal labor supply model with credit and hours frictions. While these ingredients have been considered separately in other contexts, I believe this is the first paper to consider these frictions together in a dynamic setting.

The model setup is as follows: Households receive an exogenous income stream from a main employer. In addition, households have the choice to participate in a spot market for
a second job. This second job spot market is frictional due to a fixed cost of participation that generates a notched budget set, and a household may decide not to work because of this cost. Note that it is not necessary to have a cost per se to get non-participation in a second job. As long as the household has a positive reservation wage, this alone will generate non-participation if the second job wage is lower than the reservation wage. The difference is that with costs of taking second jobs, the household also has reservation hours—a minimum number of hours the household would want to work in order to be better off than not working at all. In addition, households are assumed to have access to savings technology but have limitations on borrowing.

One way to rationalize this labor market is with implicit or long-term contracts with partial insurance (Abowd and Card, 1987; Beaudry and DiNardo, 1991; Lamadon, 2016). Because it is not the main object of interest for this paper, I leave the contracting process unmodeled, and assume that there is no dynamic incentive to deviate from the contract to seek another permanent job. This could be satisfied if households are on their labor supply curve on average, households are in the steady state, shocks are transitory, and/or there are switching costs across main jobs.

The next subsection lays out a general statement of the household problem. I make a number of standard assumptions, but relax a common assumption that consumption and hours require an interior solution. I establish a number of predictions that will then be tested in the data. In Section 6 I consider a numerical solution of the model with additional structure.

2.1 The Household Problem

At period \( t \), a representative household chooses consumption, \( c_t \), and second hours, \( h_{2,t} \), to maximize a stream of future expected utility, discounted by a factor \( \beta \in (0,1) \). Instantaneous utility, \( u(c_t, h_t) \), depends on consumption and total hours. Denote derivatives of the utility function with respect to control variable \( x \) by \( u_x \). \( u(c_t, h_t) \) is assumed to have standard
properties: $u_c > 0, u_h < 0$, with $\lim_{c \to 0} u_c = \infty$.

Households have an exogenous main job earnings process, $e_{1,t}$. Main job earnings are a function of main job hours, $h_{1,t}$ (e.g. overtime work can be paid at a higher wage). $h_{1,t}$ could be zero (unemployment). Households can borrow and save but asset positions are subject to a borrowing constraint, $A$. Denote $A_t$ as start of period assets (assets carried forward at the end of period $t - 1$), and $R_t$ the realized gross interest rate on assets between the end of period $t - 1$ and start of period $t$.

In addition, the household can access a spot market for a second job and earn an hourly wage of $w_{2,t}$. Second hours choices must be non-negative, and total hours, $h_t = h_{1,t} + h_{2,t}$, must not exceed $H$, the hours endowment. If the household participates in the second job, the household must pay a fixed cost, $\kappa$. This fixed cost can be thought of as actual outlays, such as childcare costs and transportation costs, and/or time costs like those from commuting and job search.\footnote{Cogan (1981) separately considers both fixed and time costs in a static setting. Denote time costs of work $\tau$. The period budget constraint with participation would be $R_{t+1}A_t + e_{1,t+1}(h_{1,t+1}) + w_{2,t+1}(h_{2,t+1}) - \kappa - c_{t+1}$, with total hours $h_t = h_{1,t} + h_{2,t} + \tau \leq H$. Time costs introduce a substitution effect in addition to an income effect. In practice, these costs will be difficult to separately identify from $\kappa$ when I take the model to the data unless the substitution effect is large, which is why I only focus on one summary measure.} The exogenous variables $h_{1,t}, w_{2,t}$, and $R_t$ are assumed to follow a finite-dimensional Markov process.

Assume the value function for the household’s optimization problem exists and satisfies the recursive Bellman equation. The model is summarized by the following equations:

$$V_t(A_t) = \max_{\{c_t, h_t\}} u(c_t, h_t) + \beta \mathbb{E}_t[V_{t+1}(A_{t+1})]$$  \hfill (1)

subject to:

$$A_{t+1} = \begin{cases} 
R_{t+1}A_t + e_1(h_{1,t+1}) - c_{t+1} & \text{if } h_{2,t+1} = 0 \\
R_{t+1}A_t + e_1(h_{1,t+1}) + w_{2,t+1}h_{2,t+1} - \kappa - c_{t+1} & \text{if } h_{2,t+1} > 0
\end{cases}$$  \hfill (2)

\footnote{Cogan (1981) separately considers both fixed and time costs in a static setting. Denote time costs of work $\tau$. The period budget constraint with participation would be $R_{t+1}A_t + e_{1,t+1}(h_{1,t+1}) + w_{2,t+1}(h_{2,t+1}) - \kappa - c_{t+1}$, with total hours $h_t = h_{1,t} + h_{2,t} + \tau \leq H$. Time costs introduce a substitution effect in addition to an income effect. In practice, these costs will be difficult to separately identify from $\kappa$ when I take the model to the data unless the substitution effect is large, which is why I only focus on one summary measure.}
A \leq A_t \tag{3}

h_t = h_{1,t} + h_{2,t} \leq H \tag{4}

0 \leq c_t, h_{1,t}, h_{2,t} \tag{5}

Many models from the literature can be nested in this setup. In particular, as the second-hours labor supply elasticity goes to zero, or \( \kappa \) becomes sufficiently large, or \( w_2 \to 0 \), the model becomes the standard Deaton (1991)-Carroll (1997)-style consumption model with an externally-imposed borrowing constraint, income uncertainty and labor supply that is perfectly inelastic. If \( \kappa \to 0, w_{1,t} = w_{2,t} \), and the borrowing constraint is relaxed, the model essentially becomes the workhorse intertemporal labor supply model from the labor economics literature.

2.2 Model Solution and Dynamics

The solution in any period \( t \) is a series of policy functions for consumption and second hours that define optimal behavior. Let \( c^*_t \equiv c^*_t(A_t; \Theta_t) \) and \( h^*_t \equiv h^*_t(A_t; \Theta_t) \) denote the time \( t \) policy functions for consumption and second hours, respectively, as a function of the state at time \( t \), where \( \Theta_t \) is a Markov state vector governing the exogenous variables.

Optimal consumption and hours behavior between two periods is governed by the Euler equations. There are two Euler equations, one for consumption and one for second hours. The Euler equation for consumption is standard, and given by:

\[
 u_c(c^*_t, h^*_t) = \beta \mathbb{E}_t[R_{t+1}V'_{t+1}(A_{t+1})] + \mu^A_t
 = \beta \mathbb{E}_t[R_{t+1}u_c(c^*_{t+1}, h^*_{t+1})] + \mu^A_t \tag{6}
\]

where \( \mu^A_t \) is the Lagrange multipliers on constraint (3). The first line is an immediate result of combining the first order conditions on consumption and assets. The second line follows from the Envelope condition.
Consider the impact of the borrowing constraint on consumption. If the household is borrowing constrained in \( t \), it must be that they expect the marginal utility of consumption to be lower tomorrow. The gain in marginal utility from relaxing the borrowing constraint is given by \( \mu^A_t \). Suppose the household has no access to a second job. Then consumption can only be smoothed via assets. If the borrowing constraint binds, then the household will be forced to consume less today. Utility could be improved if the household had access to a technology that could move consumption back to today.

Now, suppose the household can use labor supply to increase consumption today. Whether the borrowing constraint binds or not, if the household participates, the household will optimally choose to supply labor until the marginal rate of substitution between hours and consumption is exactly equal to the second wage. This intratemporal condition is given by:

\[
w_{2,t} = - \frac{u_{h_2}(c^*_t, h^*_t) + \mu^0_t - \mu^H_t}{u_c(c^*_t, h^*_t)}
\]  

(7)

where the link between the marginal rate of substitution may be distorted if the household is overemployed in the main job \( (\mu^0_t > 0) \) or hits the upper bound on available hours \( (\mu^H_t > 0) \). If the household has a higher marginal utility of consumption today, for instance, because the borrowing constraint binds, the denominator in (7) will be relatively high, requiring more hours to maintain equality with the wage offer. The probability constraints will bind in the future will also affect decisions today. Suppose the household gets hit with a negative shock. This means fewer assets are carried forward. If the shock has any persistence, the household expects a similar situation tomorrow. The probability that the credit constraint will bind in the future has increased. This will have an added effect of decreasing consumption and therefore increasing the hours response today. If hours are higher because the borrowing constraint binds, this will be a “second-best” response, because of the extra disutility of work. These dynamics establish the first key prediction.

**Prediction 1.** Conditional on participation, second-job hours are increasing for negative
deviations in main job hours from the steady state. A optimizing household will seek to increase labor supply by more when credit constrained.

As in Swanson (2012), assume the model has a nonstochastic steady state, defined as $x_t = x_{t+k} = \bar{x} \forall k > t$, where $x \in \{c_t, h_{2,t}, A_t, h_{1,t}, w_{1,t}, w_{2,t}, \Theta_t\}$ and further assume $w_2 < w_1$. For the household’s main job to be the optimal contract, at the steady state, the household desires no additional hours at the first job wage, $h_2^*(\bar{A}|w_{2,t} = w_1; \Theta) = 0$. Steady-state consumption and assets will depend on the primitives in the model.

At the steady state, the model has an interesting asymmetry. Because the household is assumed to be on their labor supply curve in the steady state, any increase in income will increase consumption and lower desired second hours. Since main hours are exogenous and second hours are bounded below by zero, the household will have no ability to adjust hours downward in response to positive realized deviations in main hours. If there is no change in $w_1$ (no overtime) or the increase in $w_1$ is insufficient to keep the household on their labor supply curve, then $\mu_t^0$ will bind and the household will be overemployed. In either case, second jobs will only be relevant for negative income and wealth shocks. This establishes my next testable prediction of the model:

**Prediction 2.** Second jobs are only a mechanism to smooth negative shocks to main earnings at the steady state.

Next, I turn to the fixed cost, $\kappa$, and its effect on participation in second jobs. The fixed cost enters the Euler equation inside assets, and indirectly inside the decision rules for consumption and second hours. $\partial V(A_{t+1})/\partial \kappa \leq 0$ is immediate, since a higher $\kappa$ lowers lifetime utility on any path where the household ever works in a second job and has no effect otherwise.

While the household will unambiguously have lower utility due to the costs of work, whether the costs raise or lower consumption and hours is ambiguous. To see this, note that if the household chooses to pay the fixed cost to participate, it has to work more in order to
recoup the cost (income effect). It may instead be optimal for the household to choose not to work and pay the costs and to have lower consumption and assets today. The policy rule for second hours will involve a participation decision governed by the reservation wage. The reservation wage, $w_{2,t}^R$, is defined as the minimum wage the household would be willing to accept in order to participate in the second job spot market. The household will participate only if the reservation wage is less than the prevailing second job wage, i.e. $w_{2,t}^R < w_{2,t}$. The second job policy decision, or labor supply function, can be summarized by the following three cases:

$$h_{2,t}^* = \begin{cases} 
0 & \text{if } w_{2,t} \leq w_{2,t}^R \\
h_{2,t} & \text{if } w_{2,t}^R < w_{2,t} \text{ and } h_{2,t} < H \\
H & \text{if } h_{2,t} > H
\end{cases}$$  \tag{11}

The first case in (11) depicts non-participation in the second job. This can occur for three reasons: 1) the household is at its steady state, 2) the household is overemployed and wishes to work less in the current period, or 3) the household wants to increase hours but the costs of work are sufficiently prohibitive. In the second case in Equation (11), the household

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9In the standard case without a fixed cost, the reservation wage is the marginal rate of substitution between leisure and consumption at zero hours of work. With a fixed cost, the reservation wage is given by the marginal rate of substitution at reservation hours, where reservation hours are the minimum number of hours required to work for the household to be indifferent between working and not working. Reservation hours are determined from the following cost minimization problem:

$$\min_{c_t, h_{2,t}} R_tA_{t-1} + e_{1,t} + w_{2,t}^R h_{2,t} - c_t - A_t|_{h_{2,t}=0}$$  \tag{8}

subject to

$$w_{2,t}^R = -\frac{u_{h_{2,t}}(c_t, h_{1,t} + h_{2,t})}{u_c(c_t, h_{1,t} + h_{2,t})}$$  \tag{9}

$$u(c_t, h_{1,t} + h_{2,t}) \geq u(c_t(A_t|_{h_{2,t}=0}; \Theta_t), h_{1,t})$$  \tag{10}

where $c_t(A_t|_{h_{2,t}=0}; \Theta_t)$ is the consumption solution with no second hours that satisfies the Euler equation, $A_t|_{h_{2,t}=0} = R_tA_{t-1} + e_{1,t} - c_t(A_t|_{h_{2,t}=0}; \Theta_t)$ are the optimal assets brought forward in this case, and $u(c_t(A_t|_{h_{2,t}=0}; \Theta_t), h_{1,t})$ is the current period utility from not participating in the second job at time $t$ given the state. Evaluated at the solution, Equation (8) will be just tangent to the indifference curve at reservation hours with slope equal to the reservation wage.
becomes a multi-job holder. The household bears the costs of work, and chooses second-job hours to equate the marginal rate of substitution between work and consumption equal to the wage. The final case is when the household still wants to work more, but is limited by the upper bounds on their time.

This labor market for a given biweekly pay period is illustrated in Figure 2. In each panel, the household is assumed to start the period with a different draw of main income. The budget constraint is shown by the thick black lines, and the thin dashed curves represent indifference curves. In Panel (a), the household works 62 hours at the main job. Point A is the (total hours, consumption) bundle at 0 second job hours. The household could also choose to pay the fixed cost and take a second job. In this case, the optimal decision will be to work and consume at point B and save the amount given by the vertical distance between the budget constraint and point B. By definition of the optimum, the marginal rate of substitution at this point is just equal to the second job wage, illustrated by the thick dashed line through point B. Point C is the point where the household is indifferent between not working, and working and paying the fixed cost. The reservation wage is represented by the absolute value of the slope of the thick dashed line that passes through C. Because the reservation wage is higher than the second job wage, the household will optimally behave by choosing not to work, point A.

Panels (b) and (c) illustrate two cases with second job participation. In these panels, the household has a smaller main earnings draw than in Panel (a). In both cases, the marginal rate of substitution is greater than the reservation wage, so the household chooses to participate. In Panel (b), the household will achieve lower current period utility, because the household will optimally choose to save a substantial amount of current period earnings and carry it forward to the next period. In Panel (c), the household achieves higher utility in the current period as well.

Define “underemployment” when it is not optimal to work only because of the costs of work. For a given $\kappa > 0$, define a “small” shock as a shock for which it is not optimal for
the household to pay the fixed cost of participation. Accordingly, the household will not use labor supply to insure against the shock and will only smooth by adjusting consumption/assets. As assets fall (for instance, following a series of negative shocks), or if the shock is “large”, the household may reach a point where $w_{2,t} > w_{2,t}^R$. If $\kappa$ falls, the reservation wage for taking a fixed cost falls, reducing the region of inaction. This is the third key prediction of the model.

**Prediction 3.** Costs of work lead to a region of inaction for “small” shocks. Accordingly, eliminating fixed costs will increase labor supply responses to these shocks and reduce consumption volatility.

To summarize the model: households smooth shocks by adjusting consumption (hence assets) and second job hours. Credit constraints limit the ability to smooth via borrowing, and will make labor supply adjustments more important. Labor supply frictions (modeled here as fixed costs of second job employment) will hamper the ability to adjust via labor supply. Reductions in costs of second employment will lead to increased consumption and second hours, and a reduction in consumption volatility, as the ability to smooth “small” income shocks increases. In the next sections of the paper, I take these model predictions to the data.

## 3 Data

Sources of data on rideshare drivers are currently limited. This paper employs a unique, transaction-level dataset from a large financial aggregation and bill-paying computer and smartphone application (henceforth, the “app”). A strength of these data is that they include high frequency income, spending and assets.

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10 These same data have previously been used to study the high frequency responses of households to shocks such as the government shutdown (Gelman et al., 2015), anticipated income (Gelman et al., 2014), and the 2014 fall in gasoline prices (Gelman et al., 2016); similar data have been used to survey the gig economy (Farrell and Greig, 2016) and understand the consumption response to debt (Baker, forthcoming).
Users of the app can link almost any financial account, including bank accounts, credit card accounts, and utility bills. Each day, the app automatically logs into web portals for a user’s accounts and obtains the user’s account balances and daily transactions. Spending transactions are available beginning December 2012. Asset data are available beginning August 2013. The app had approximately 1.4 million active users in the U.S. in 2013, and approximately 18,000 households have any rideshare income over the period 2012-2016.

A number of sample restrictions need to be made before proceeding with analysis. The most important restriction is that households must be observed for a period before starting rideshare (the “pre period”). A household can sign up for the app after starting ridesharing, which would mean they would only be observed in a “post period.” Since rideshare work can sometimes have gaps between weeks worked, I choose 6 weeks of lead time as my cutoff. Many households sign up for rideshare and appear to drop out soon thereafter: perhaps they have learned that it is unsuitable for them. I restrict the sample to households that have some attachment to ridesharing. The sample is restricted to households with 6 or more weeks between first and last observed rideshare pay. The sample is comprised of 10,316 rideshare drivers after this restriction is made.

I also focus on a second subsample of workers with stable, biweekly employment (i.e. paid every 14 days), with identifiable main employers. This subsample is important for two reasons. First, most households in the U.S. are paid biweekly. Second, because I can identify employers, I am able to find coworkers of rideshare drivers at their same primary (non-rideshare) employers. These matched coworkers are useful for identifying common trends. Further, coworkers can be used to identify a firm-level income process that is a plausibly-exogenous source of variation in main payroll income, driven for instance by firm productivity shocks.

This subsample includes 2,217 drivers. While the sample size is considerably smaller, this does not imply that only 22 percent have stable jobs over the period around starting rideshare. First, I only keep households with regular biweekly income, therefore dropping
weekly and monthly earners. In addition, I cannot identify employers when a transaction string in the app data does not contain a keyword associated with payroll income. Appendix B describes further how I construct the main samples used in estimation. Appendix C contains results for additional sample restrictions, such as focusing on all workers with non-zero payroll income within a month, instead of just strict biweekly earners.

One obvious concern with data from an online app like this one is that the data are not representative or the sample is composed of households that are more financially sophisticated than the general population. Gelman et al. (2014) discuss the demographics of the sample in more detail and find that the population in the app data is heterogeneous and broadly in line with US demographics. In addition, Gelman et al. (2016) compare the consumption behavior of the whole sample to consumers in the CEX and find that total consumption and gasoline spending in the app and CEX line up closely. The app data notably exclude poor “unbanked” households. While this is a potential concern in other contexts, it is not relevant for this study, because rideshare drivers must have late model cars and receive direct deposit, making a bank account a virtual requirement for becoming a rideshare driver. Effects of app usage on household behavior are another concern. Baker (forthcoming) compares “active” users—users who use the app frequently—with “passive users”—users who sign up but do not use the app frequently. He finds these users have similar consumption behavior, suggesting that intensity of app usage does not change consumer behavior on average.

3.1 Descriptive Statistics

Table 1 provides descriptive statistics on variables well-measured in the app data: income, assets and spending. I provide statistics on the cross-sectional averages and medians of total spending, total income, payroll income, bank balances, credit card (CC) balances, credit card utilization rates (credit card balances divided by credit limits), and net balances (bank balance net of credit card balance). For spending and income, I calculate each individuals’
time-series standard deviation and report the cross-sectional averages and medians over all individuals. I also provide descriptive statistics on the census region of the closest city where Uber operates.\footnote{User location is determined from the most common city where gasoline spending occurs. In a small number of cases where location cannot be scraped from gasoline transaction strings, I default to the location of the user's IP address}

Columns (1) and (2) of Table 1 show the descriptive statistics, pre- and post- starting rideshare, for the full sample of ever-rideshare drivers satisfying the sample selection criteria discussed in the previous subsection. Columns (3) and (4) show the same weekly values for the biweekly job-holder subsample with identifiable main employers.

Comparing log spending and its standard deviation across rows, the subsample of regular biweekly earners have higher and less volatile spending than the full sample. Comparing pre and post, spending rises and the standard deviation of spending falls for both groups. Average and median total income is higher for the biweekly earners, mainly due to differences in payroll income. One important difference between the full sample and the subsample is how payroll income changes over the pre and the post period: While payroll income declines for the full sample in the post period, there is no significant change in average or median payroll income for the biweekly earners. The typical rideshare driver is in debt between $950 and $2,519 across the periods, and credit card balances rise for both groups over time. Overall, net balances (bank balances net of credit card balances) deteriorate over the periods.

Table 2 provides descriptive statistics for the biweekly job-holder subsample where asset values are taken the day before receipt of biweekly pay and spending is calculated in the 14 days following receipt of biweekly pay. Column (3) of this table provides the descriptive statistics for 468,365 matched coworkers at the same employers. Appendix B.1.3 describes how the sample of matched coworkers is constructed. Because payroll income is never zero for the groups in Table 2, I also include log values of income in the table.

Interestingly, log spending of ever-rideshare drivers is 12-17 percent higher than coworkers in the pre-period. Log payroll income is similar to the coworkers, but log total income is
5-7 percent higher for ever rideshare drivers comparing pre-period values, suggesting ever
rideshare drivers may be more likely to earn income outside of the main job than coworkers.
Note that both the ever-rideshare drivers and their coworkers have large volatility in income
and spending—the average and median time-series standard deviation of biweekly log payroll
range between 17 and 23 percent.

Asset and credit variables show the most striking differences. Ever-rideshare drivers with
regular biweekly earnings in the pre-period have less in the bank than coworkers, and more
credit card debit. Median credit card utilization in the pre period is 13 percentage points
higher than coworkers. Median net balances of ever-rideshare drivers on the day before the
paycheck are negative $1,235 in the pre-period and -$1,758 in the post-period, compared to
-$490 for the median coworker. This finding is in line with Prediction 1 of the model, which
stated that second labor supply will be increasing as assets decline.

While the app data provide rich, high frequency data on consumption, income and assets,
there is only limited demographic information available. Other work using tax data (Jackson,
Looney and Ramnath [2017], and survey and internal data from a popular ride-sharing
platform (Hall and Krueger [2016]), can be referenced for more detailed demographics specific
to rideshare drivers. Briefly, the population is more likely to be male and young (although
there are more women and older workers when compared to taxi drivers). In 2014, 46 percent
were married, 44 percent had children and the mean (median) age was 40 (38) (Jackson,
Looney and Ramnath [2017]).

\section{Research Design}

This section presents my research design. In Section 4.1 I introduce an event-study framework
to examine the evolution of key variables around starting rideshare. I next discuss my
research design for the subsample of continuously employed biweekly earners in Section 4.2.
I then turn to consumption smoothing. I present a differences-in-differences framework mea-
suring how the “partial insurance” parameter from Blundell, Pistaferri and Preston (2008) changes around starting rideshare. An instrumental variables strategy for addressing endogeneity of main income using firm shocks and endogenous selection into rideshare using Uber’s launch is discussed in Section 4.3. Finally, a number of measurement concerns that are particular to high-frequency data, such as shopping and inventory behavior, are discussed in Section 4.3.3.

As in other related studies, the main estimates will be “Treatment-on-the-Treated” (TOT) effects. Only those households that have a benefit from ridesharing employment will select in. On one hand, we might expect the treatment effects of ridesharing to be largest for the treated since they chose to join rideshare. On the other hand, there are potentially positive treatment effects in the rest of the population as well. Information frictions and other frictions prevent participation, such as credit frictions that prevent a car purchase. Finally, the benefits may be time-varying: households that do not select in now could be hit with an income shock at a later time that could make them participate.

4.1 Event Study Framework

Event studies provide a non-parametric way of exploring the evolution of key variables around starting rideshare. The event-study specification I use is standard and given as follows:

\[ y_{it} = \sum_{k \in K} \beta_k D_{it}^k + \alpha_i + \alpha_t + \epsilon_{it} \]  

12There are actually three different events of interest: (1) Uber entry into the local geographic market, (2) signing up for Uber, and (3) first rideshare income. While (1) is the true exogenous event, in reality, information about Uber entry will take time to spread to households, which makes Uber entry not a precise event date. The typical driver in my sample begins driving for rideshare over 1 year following Uber’s entry into a market. Event (2) can be proxied with account verification deposits discussed in Appendix B. Receiving an account verification suggests the household has applied for driving for Uber. A gap between verification and first income could be indicative of multiple things. First, it could suggest that households are waiting to use rideshare for the first time, perhaps due to an expected future income shock unobserved to the econometrician. Alternatively, there may be a small amount of uncertainty about whether a car or a background check might be approved (although according to Uber, denials are relatively rare). In either case, there is an expected probability of future income, and so consumption theory would suggest that consumption would rise on this expectation. However, what I find is that spending jumps only upon receipt of income, not upon income verification. This motivates my use of receipt of income as the event date.
where $y_{it}$ is the dependent variable of interest. $a_i$ is an individual fixed effect, and $\alpha_t$ is a time fixed effect (calendar week for the weekly sample, actual paydate for the biweekly sample). $D^k_{it} = \mathbb{I}\{t = E_i + k\}$ is a dummy indicating time to first rideshare pay, $E_i$, with negative $k$ indicating a future event date, and positive $k$ indicating the event occurred $k$ periods in the past. In specifications that are run at the weekly frequency, I omit the indicator for the time period two weeks before first rideshare earnings (1 week prior is the week the household would have worked in order to receive income in period 0). The $\beta_k$ coefficients are then relative to the week before the household started working as a rideshare driver.

In specifications with a control group, the control group has $D^k_{it} = 0$ for all $k$. The control group adds precision to the estimates of $\alpha_t$. If the control group is on a different trend than the ever-rideshare drivers, we can discern this by comparing the estimated pretrends with and without including the control group.

By construction, the sample is balanced 6 weeks prior and 4 weeks post the event. Outside of this window, the sample can become unbalanced. When the sample is not balanced, interpreting the coefficients when few observations are identifying them must be done with caution. As is conventional, the standard errors are clustered at the unit which receives the “treatment.” In my baseline specification, this is the household. In other specifications, I will cluster on either firm and city, depending on the source of variation.

4.2 Consumption Responses to Income Pre- and Post- Rideshare

The sensitivity of rideshare income and consumption spending are important moments from the model. Of course, rideshare income is only observed in the post period. Although other sources of second income can be observed earlier, other second jobs are difficult to observe in the data, particularly if pay is received in cash or check, rather than direct deposit. On the other hand, household spending can be observed in both the pre and post periods. This allows me to use a differences-in-differences research design for spending. For the specifications that follow, I focus on the sample of biweekly earners with no break in their employment, so that
estimates capture responses to the typical biweekly earnings process faced by most workers. My differences-in-differences research design for this sample is discussed next. Threats to identification are discussed in section 4.3.

### 4.2.1 Consumption and Income Smoothing

Following Blundell, Pistaferri and Preston (2008), a summary measure of “consumption insurance” is a household’s consumption response to income deviations. Consider the following specification:

$$\text{Log Spending}_{i,t} = \delta_1 \text{Log Main Pay}_{i,t} + \gamma_i + \gamma_t + \epsilon_{it}$$

where in my case Log Spending$_{i,t}$ is log total spending net of auto expenditures, Log Main Pay$_{i,t}$ is log payroll earnings from the main job, and $\gamma_i$ and $\gamma_t$ are individual and time fixed effects, respectively. By construction, my sample contains households who have non-zero spending in a biweekly period, so the dependent variable is well defined.

Because this is a log-log specification with individual and time fixed effects, we can interpret $\delta_1$ as the elasticity of spending with respect to changes in main payroll income. This specification can be motivated by a log-linearized version of the consumption Euler equation (see Blundell, Pistaferri and Preston, 2008). In the reduced-form, $\delta_1$ tells us about the degree of partial “insurance” from income volatility. A value of “0” implies full insurance for payroll income volatility, while a value of “1” implies no insurance.

In Blundell, Pistaferri and Preston (2008), the main mechanism driving changes in consumption smoothing behavior is postulated to come from two sources: changes in the time-series properties of shocks and increased credit intermediation. The authors estimate elasticities of consumption with respect to transitory shocks and permanent shocks of 0.05 and 0.64, respectively. The key idea in my paper is that changes in households’ ability to adjust

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13 Auto expenditures include spending on gasoline and at auto body repair shops. These expenditures are identified using a machine learning classification algorithm discussed in Appendix B.1.
their labor supply due to technological change will lead to increased consumption smoothing (Prediction 3 of the model.)

As a way to capture this mechanism, consider a differences-in-differences version of Specification (13), that includes an indicator for when a household starts driving for rideshare, Post Rideshare\(_{i,t}\), and an interaction between Log Main Pay\(_{i,t}\) and Post Rideshare\(_{i,t}\), as follows:

\[
\text{Log Spending}_{i,t} = \delta_1 \text{Log Main Pay}_{i,t} + \delta_2 \text{Post Rideshare}_{i,t}
+ \delta_3 \text{Log Main Pay}_{i,t} \times \text{Post Rideshare}_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t}
\] (14)

The \(\delta_3\) coefficient is interpretable as the change in “insurance value” after starting ridesharing. In specifications with a control group of coworkers, \(\delta_1\), which tells us about smoothing in the pre-period, will also be identified off of the control group. The control group might have a differential spending response to payroll income because they have more assets or a different earnings process. We can explicitly test for this by interacting Main Pay\(_{i,t}\) with an indicator for being an ever rideshare driver. Denote this indicator Ever Rideshare\(_{i,t}\).

Prediction 2 of the model stated that households will become more insured against negative shocks. To test this prediction, we can augment Specification (14) with an indicator for receiving a negative income deviation. My procedure to identify negative deviations involves two steps. Step 1 is to residualize the covariates from individual and year fixed effects—denote these residuals \(\tilde{\text{Main Pay}}_{i,t}\). These are within-year deviations, picking up seasonal variation in demand, etc. Using the residualized variables in a regression will yield the same coefficients as Specification (14) (Frisch-Waugh-Lovell theorem). I next identify negative residuals, \(\text{Neg}_{i,t} = I\{\text{Main Pay}_{i,t} < 0\}\). Step 2 places these residuals in the main
specification. The expanded differences-in-differences specification is shown below:

$$\begin{align*}
\tilde{\text{Log Spending}}_{i,t} &= \delta_1 \tilde{\text{Main Pay}}_{i,t} + \theta_1 \tilde{\text{Main Pay}}_{i,t} \times \text{Neg}_{i,t} \\
&\quad + \delta_2 \tilde{\text{Post Rideshare}}_{i,t} + \theta_2 \tilde{\text{Post Rideshare}}_{i,t} \times \text{Neg}_{i,t} \\
&\quad + \delta_3 \tilde{\text{Main Pay}}_{i,t} \times \tilde{\text{Post Rideshare}}_{i,t} + \theta_3 \tilde{\text{Main Pay}}_{i,t} \times \tilde{\text{Post Rideshare}}_{i,t} \times \text{Neg}_{i,t} \\
&\quad + \theta_4 \text{Neg}_{i,t} + e_{i,t}
\end{align*}$$

(15)

$\delta_1$ ($\theta_1$) now captures the household’s response to positive (negative) deviations, and $\delta_3$ ($\theta_3$) estimates how the response to positive (negative) shocks changes in the post period. Because the regressors are generated from a first step, I calculate clustered bootstrapped standard errors over the two steps.

### 4.3 Identification

There are two main endogeneity issues that must be addressed before interpreting the results as the causal effect of starting rideshare: endogeneity in main job income and endogenous selection into rideshare. These concerns and an instrumental variables design to address them are discussed next.

#### 4.3.1 Endogenous Main Income

Specifications (13)-(15) examine main income as a right hand side variable. One concern is that the household income process may have an endogenous component that is correlated with the dependent variable. In the standard intertemporal labor supply model, for instance, hours in the main job are assumed to be under control at all times. Even if this is not the case, it is reasonable to assume that households still exert at least some control over weeks worked at some points in the year, e.g. they can choose to go on vacation. In this example, consumption spending will increase, but income will stay flat if the household has paid vacations, and may fall if overtime or other earning opportunities are foregone. In addition,
some endogenous reasons impacting hours in the first job, such as taking a sick day or going on vacation, will also spill over to the second job.

My instrumental variables design to deal with this issues uses the firm component of main income as an instrument for individual income. Consider the following specification for log main pay additively separable in firm and individual components:

\[
\text{Log Main Pay}_{it} = \beta \text{Log Main Pay}_{J(i),t} + \alpha_i + \alpha_t + \zeta_{i,t}
\]  

(16)

where \( J \) indexes firms. \( \text{Log Main Pay}_{J(i),t} \) is the firm component of the current period income, which can be driven by productivity shocks, \( \alpha_i \) is an individual fixed effect capturing individual ability, \( \alpha_t \) is a common aggregate movement, and \( \zeta_{i,t} \) is the individual’s idiosyncratic component specific to the pay period.

In practice, I consider a leave-out mean \( \text{Log Main Pay}_{J(i),t} \), so that the instrument is not biased by the individual’s earnings. Figure 3 illustrates the first stage by comparing an individual’s own income deviations against this leave out mean. The regression coefficient is 0.404 and the F-statistic is over 200. This confirms that common movements in firm income are a large source of variation in biweekly earnings.

### 4.3.2 Endogenous Participation Decision

Even though the decision to drive for rideshare is first determined by rideshare entry into the market, the household can choose to drive anytime thereafter. While non-time-varying level differences can be controlled for via household fixed effects, idiosyncratic variation in assets and income likely influence the decision of when to start driving as well as consumption levels and consumption smoothing. My research design to deal with this issue exploits the staggered geographic entry of rideshare platforms into different markets.

Consider an expected, idiosyncratic, and permanent decline in income at time \( t + 1 \) that induces a household to drive for rideshare at time \( t \). The counterfactual is lower future con-
umption. If the household drives for rideshare and only makes up 50 percent of the earnings losses, we would attribute a negative treatment effect to starting rideshare. Pretrends in the event study results can be used to assess the scope of endogeneity in the participation decision. For instance, we might expect to see an “Ashenfelter” dip, where a variable trends downward in the weeks before starting rideshare. In the event study results, the treatment effect might instead require comparing post outcomes to an earlier period, rather than the period right before starting rideshare. If the household chooses to start driving simultaneous to an income shock, or preceding an expected income shock, then this will not be discernible from the pretrends. Endogenous participation is also a problem in Specifications (14)-(15) because if the household starts the period with lower assets, they will have higher MPC’s out of current income. This will bias the estimates towards finding smaller consumption-smoothing benefits (or even less smoothing in the post period), particularly in short panels.

Suppose the household has the following model for the rideshare participation decision:

\[
\text{Post Rideshare}_{it} = \beta \text{Uber Launch}_{c(i),t} + \alpha_i + \alpha_t + \epsilon_{it} \tag{17}
\]

where Post Rideshare\(_{it}\) = 1 following a household’s decision to start rideshare employment, and 0 otherwise, Uber Launch\(_{c(i),t}\) = 1 following Uber’s entry into the local market, \(c\), and zero otherwise, \(\alpha_i\) is an individual fixed effect reflecting individual distaste for driving, distance to the market, etc, and \(\alpha_t\) is a time fixed effect capturing aggregate determinants of entry. \(\epsilon_{it}\) may contain current or future income shocks which may be in the information set of the household at time \(t\) but unobservable to the econometrician.

Equation (17) introduces my instrument for the decision to drive: rideshare launch into the market. The maps in Figure A10 show the spatial time series of when the largest rideshare platform, Uber, launched in a new city. While my empirical results use total rideshare earnings, here I use Uber’s launch dates. As shown in Figure I, Uber is the largest rideshare platform and operates in the most markets. Moreover, conditional on being an
Uber drivers, 93.3 percent of rideshare earnings come from Uber. Conditional on being a Lyft driver, 33 percent of earnings come from Uber. The exclusion restriction is that rideshare decision to enter the market is exogenous to household consumption decisions. Market size and idiosyncratic reasons such as the friendliness of local governments were key factors in Uber’s entry choices. These reasons are unlikely to be related to individual consumption growth paths, suggesting the instrument is valid.

In specifications with a control group, the indicator for Uber’s launch, Uber Launch\(_{c(i),t}\), will be a weak instrument, given the probability of driving for rideshare is relatively low, less than 1-2 percent. Because whether someone takes up the treatment is observed, I proceed by instead studying the interaction with an indicator for being an ever-rideshare driver: Rideshare Launch\(_{c(i),t}\) × Ever Rideshare\(_{i,t}\). This will not yield an ATE because the decision to drive for Uber is not random. However, the decision of when to drive for Uber is now exogenous. When the control group consists of coworkers, they only help to identify the time-fixed effects. As with any specification comparing means pre and post, a parallel trends assumption must hold for the identification strategy to be valid.

We can combine the instruments for both income and Uber’s launch to instrument Specification (14). The first stage is given by:

\[
\begin{bmatrix}
    \text{Log Main Pay}_{it} \\
    \text{Post Rideshare}_{it} \\
    \text{Log Main Pay}_{it} \times \text{Post Rideshare}_{it}
\end{bmatrix} = Z\delta + e_{i,t} \tag{19}
\]

where \(Z\) is a block diagonal matrix with the instrument set on each of the diagonal elements.

\(^{14}\)Since both Post Rideshare\(_{it}\) and Uber Launch\(_{c(i),t}\) are binary, the estimated coefficient in Equation (17) is a Wald estimator. In a simple regression framework, this estimator is as follows:

\[
\beta_{Wald} = \frac{E[y_{it}|\text{Uber Launch}_{it} = 1] - E[y_{it}|\text{Uber Launch}_{it} = 0]}{E[\text{Start Rideshare}_{it}|\text{Uber Launch}_{it} = 1] - 0} \tag{18}
\]

Here, the numerator is the difference in means of the dependent variable pre- and post- Uber’s entry into the market and the denominator is the average share of possible periods working for rideshare. Because I consider a regression with individual and time fixed effects, identification comes from across households in other cities that have yet to receive access to ridesharing.
ments equal to $\text{Uber Launch}_{c(i),t} \times \text{Ever Rideshare}_{i,t}$, Coworker Earnings $J(-i),t$, Coworker Earnings $J(-i),t \times \text{Uber Launch}_{c(i),t}$, Coworker Earnings $J(-i),t \times \text{Ever Rideshare}_{c(i),t}$, $\alpha_i$, $\alpha_t$, $\delta$ is a column vector of stacked coefficients specific to each endogenous variable, and $e_{i,t}$ is a vector of independent error terms for each endogenous variable.

4.3.3 Measurement Issues

The *consumption*-smoothing benefit of flexible labor supply is the key object of estimation in this paper. The app data do not contain “true” consumption, but rather expenditures. Suppose current period expenditure is given by the following accounting identity:

$$E_{it} = C_{it} + D_{it} + \zeta_{it}$$

where $E_{it}$ is expenditures, $C_{it}$ is true consumption, $D_{it}$ represents spending which generate a flow value of utility but is not instantaneous consumption, like durables purchases, inventory purchases and bill pay, and assume $\zeta_{it}$ is all other expenditures, some of which may or may not be consumption (such as taxes). Note, each component of expenditures will also affect assets in the same way as consumption.

To test whether a relationship between inventory/shopping behavior is driving results, I consider two robustness checks: (1) including leads and lags of spending in the main regressions and (2) aggregating to lower frequencies following Coibion, Gorodnichenko and Koustas (2017). If these robustness checks have a limited effect on my main parameters of interest, this suggests a very weak link between inventory behavior and income (i.e. $\text{cov}(D_{it}, \text{Log Main Pay}_{it} \approx 0)$). Other factors, such as whether an item is on sale, likely play bigger roles. In this case, if $D_{it}$ and $\zeta_{it}$ are orthogonal to true consumption, they will effectively be measurement error. As is well known, measurement error in the dependent variable will inflate standard errors.

In addition, I do not observe hours, only income. Total rideshare earnings can include
bonuses and incentive pay from rideshare providers. This will also be treated as measurement error in my framework. Many of these bonuses are incentives to sign up for ridesharing and fade away over time, and so they should not affect long-run outcomes.

5 Empirical Results

The main empirical results are presented in this section. The event-study results for the full sample are found in Section 5.1. Section 5.2 focuses on the sample of continuously-employed biweekly earners. I present the event-study results for this subsample, before exploring consumption smoothing results in Section 5.2.1.

5.1 All Ever-Rideshare Drivers

I begin with a graphical presentation of the event study results for the full sample of ever-rideshare drivers. In all event study figures (Figures 4-6), the dashed vertical lines indicate that the area between the coefficients are estimated on a balanced sample. 95 percent confidence intervals are shown in dashed gray lines around the main estimates.

Panel (a) of Figure 4 shows the event-study results for gasoline spending, measured in dollars. Recall, the coefficients are all relative to the period two weeks before first rideshare pay. Gasoline spending begins to rise 1 week before the first rideshare pay. This happens because first rideshare pay is received with a lag of one week after starting to work. Gasoline spending peaks one week later at a $19 increase, and then declines over time. Gas prices fluctuate a great deal over this period, but assuming an average gasoline price of $2.50, this is about 7.6 gallons of gasoline. The average car in the US at this time received about 21.5 miles to the gallon, implying that the average rideshare driver drove about 160 miles in the week.

In this figure, I overlay the probability of receiving rideshare pay in any week (red line

with hollow marker). The decline in gas spending lines up closely with the decrease in the probability of working in rideshare in that week. About 1 month later, only around 60 percent are working. Recall that I restrict the sample to having last observed rideshare pay at least 6 weeks after the first payment, so this decline is not driven by quitters.

Panel (b) of Figure 4 plots the event-study coefficients for log total spending excluding automobile expenditures. In contrast to gasoline consumption, non-gasoline consumption appears not to jump until the week with receipt of income.\textsuperscript{16} The pre-event coefficients shows a small positive pretrend over the 3 months prior to starting rideshare. Two weeks after receiving the first rideshare pay, spending increases by about 10 percent. However, the benefits fade over time. The underlying reason will be made clear after examining the income process.

Before turning to income, I break down spending into component categories. I run separate event studies for different categories of goods. Since most categories have many zeros, the dependent variable is in dollars. The event-study coefficients for 6 weeks pre and 1 week post are shown in Table 3. I choose to report these coefficients because 6 weeks pre is the earliest period for which the sample is balanced, and 1 week post is the period where spending peaks, and so it is interesting to see where households are spending this money. The table shows total spending rises by 74.42 one week after first rideshare pay. The negative coefficients 6 weeks pre on services and parts implies spending increases around starting rideshare by about $6 per week on average. In the post period, the household increases fast food spending by about $2.8 per week on average. While this might be partly a non-separability (because of increased work schedules, the household substitutes towards fast food), grocery and restaurant spending also increase, suggesting households increase overall food spending. In addition, clothing and electronics spending are higher relative to two weeks before starting rideshare.

\textsuperscript{16}I have also separately examined results using the account verification date discussed in Appendix B as the event date (not shown). If we examine households that have at least one week gap between income verification and first income, consumption does not jump until the week income is received. This appears consistent with a large literature on expected income shocks (e.g. Johnson, Parker and Souleles 2006).
In the next set of figures, I focus on the income process. Because the typical income process is biweekly, I aggregate income over two week periods. Panel (a) of Figure 5 focuses on total income, in levels, to accommodate $0 income. Panels (b) and (c) focus on payroll income, excluding rideshare income. The dependent variable in Panel (b) is an indicator for any payroll income, while Panel (c) focuses on payroll income in dollars (again, so that zeros are included).

While Panel (a) shows increases in total income, Panels (b) and (c) show large, persistent declines in main payroll income in the period surrounding rideshare takeup. Panel (b) shows that two months prior to starting rideshare, the percentage with payroll income was about 3 percentage points higher than the period right before starting rideshare. One quarter after starting rideshare, the share with payroll income is about 6 percentage points lower. Thus, the total decline in the share having any payroll income around starting rideshare is around 9 percentage points. While we cannot know for sure whether the income losses are voluntary or not, income appears to begin falling many weeks prior to rideshare takeup. This suggests that the household is not substituting away from the main job specifically to take up a rideshare job. Panel (c) shows payroll income in dollars, and therefore accounts for changes in income coming from both the intensive and extensive margins. One month prior to starting rideshare, income was about $50 higher; the fall in average payroll income mirrors the decline in the probability of working in Panel (b). Comparing one quarter pre rideshare takeup with one quarter post takeup, the total decline in payroll income is $174. On this figure, I also overlay average rideshare earnings minus auto expenses (gasoline and car service/repair). Average rideshare earnings net of expenses peak at about $250, and decline to $126 per week after a quarter. When compared to the income results, this suggests that on average rideshare replaces about 73 percent of the decline in main job earnings.

Event studies for the household balance sheet are shown in Figure 6. Panel (a) shows the result for bank balances. Panels (b) and (c) show the result for credit card utilization and credit card balances, respectively. The result in Panel (d) shows net balances (bank balances
minus credit card balances). Taken together, these pictures tell a consistent story: households are running down assets and racking up credit card debt prior to starting rideshare. After starting rideshare, these balances stabilize.

5.2 Results for continuously employed, biweekly earners, with matched-coworkers

A key finding from focusing on all ever-rideshare drivers is that rideshare participation follows large, persistent drops in main income, with non-employment increasing by about 9 percentage points. This result makes clear that the full sample faces a mix of transitory and permanent shocks. Focusing on the continuously employed rideshare drivers and on transitory shocks can avoid this complication.

Event study results for continuously employed, biweekly earners are shown in Table 4. In these results, coworkers at the same employers are included as a control group. The control group is weighted using inverse-propensity score weights, matching on 2013 income and assets, and accordingly only includes coworkers that were in the data in 2013. Further details of the weighing procedure can be found in Appendix B.2. The counterfactual is that consumption behavior of these rideshare drivers would have evolved similarly in the absence of rideshare income. To compare results across specifications, I bin together coefficients for the pay periods ending in the following windows around first rideshare pay: 90+ days before, 31-90 days before, 1-30 days before, 0-30 days post, 31-90 days post and 90+ days post. In addition, I normalize balances by average daily spending, to address some of the wide dispersion in assets. I omit the period 1-30 days prior to starting rideshare, so results are relative to this period.

Column (1) shows the results for log spending net of auto expenses. There is no evidence of any pretrends for consumption spending, suggesting parallel trends with the control group of coworkers. In the long-run, consumption spending is approximately 2.5 percent higher. Columns (2) and (3) show the results for total income and payroll income, respectively. This
group has a slight downward trend in total income in the pre-period, driven by declines in payroll income: 90+ days earlier, total income was about 2.2 percent higher, and payroll income was 2.6 percent higher. Bank and credit card balances (Columns 4-6) also seem to be deteriorating from 90+ days earlier. Because I normalize these balance sheet variables by average daily spending, the interpretation of the coefficients is in terms of days of spending. In payperiods ending 90 days prior to starting ridesharing, the household had about 2 more days of typical consumption in liquid assets. In the immediate post period, the household has about 1.4 days fewer assets. Liquid assets improve as time goes on. Assets in the period 31-90 days after starting rideshare and are not statistically different from the period 31-90 days prior.

5.2.1 Results: Consumption Smoothing

This section focuses on household consumption-smoothing behavior. I begin with a series of results based on Specification (14). Column (1) of Table 5 includes inverse-propensity score weights discussed in Section B.2 as well as individual fixed effects and year fixed effects. The coefficient on Log Main Pay refers to the elasticity between spending and income in the pre-period for coworkers and is estimated to be 0.3. This estimate is very precise, because it is also identified off of the control group of coworkers. The coefficient on the interaction Log Pay_{i,t} \times Ever Rideshare_{i,t} provides a test for whether ever-rideshare drivers have a different sensitivity of spending to earnings. This coefficient suggests ever-rideshare drivers are slightly worse at smoothing, having a total responsiveness of spending to income 3.9 percentage points higher. The key coefficients of interest are on Post Rideshare_{i,t} \times Log Pay_{i,t} and Post Rideshare_{i,t}. The coefficient on Post Rideshare_{i,t} \times Log Pay_{i,t} implies that spending becomes 6.8 percentage points less sensitive to main income in the period after starting rideshare. The coefficient on Post Rideshare_{i,t} tells us about the increase in spending if Log Pay_{i,t} were evaluated at 0 (an out of sample prediction for this group of employed workers). The implied increase is large, 53.8 log points.
Moving to the right are different robustness checks. Column (2) is a more parsimonious specification, dropping the interaction between Log Pay_{i,t} × Ever Rideshare_{i,t}. The main interaction on Post Rideshare_{i,t} × Log Pay_{i,t} falls slightly, by about 1 percentage point, and the effect on Post Rideshare_{i,t} also falls, suggesting that by not allowing for different pre-period smoothing between rideshare drivers and coworkers will underestimate the benefits of rideshare income. Column (3) drops the weights. This strengthens the effect on Log Pay_{i,t} by about 0.7 percentage points, but the results on the other coefficients are similar to Column (2). Column (4) adds in paydate fixed effects to the specification in Column (1). The results are very similar to Column (1). Overall, the coefficients are stable as we move across the rows.

Column (5) instruments Log Pay_{i,t} in the regression in Column (3) with average log coworker earnings, Coworker Earnings_{i,t}. Log Pay_{i,t} in the interaction is also instrumented. The coefficient on Log Pay_{i,t} rises by 6.2 percentage points, suggesting that households are worse at smoothing firm payroll shocks. The post-period benefits of rideshare increase. The decline in the sensitivity of spending to income is now 9 percentage points. Summing rows (1) and (3) suggests a responsiveness in the post period of 0.2822, slightly higher than the comparable sum of 0.25 in Column (3). Standard errors are clustered on the firm; as a result, the finding is less precise, with a standard error over two times larger than Column (3). While we can reject the pre-period smoothing is the same, the equality of consumption smoothing in the post-period cannot be rejected.

The next set of results shown in Table 6 are based on Specification (15) in the text. These results test a key prediction of the model, that households will be better able to smooth negative deviations. \( \tilde{\text{Post Rideshare}}_{i,t} \times \log \text{Pay}_{i,t} \) now refers to the change in response to positive shocks in the post period. The new key coefficient of interest is on \( \tilde{\text{Post Rideshare}}_{i,t} \times \log \text{Pay}_{i,t} \times \text{Neg}_{i,t} \), which tells us about the household’s response to negative deviations in income. Column (1) is the result from Column (3) of Table 5. Column (2) uses the control group for identification of the pre-period responses, while column (3)
interacts all the coefficients shown in the table with an Ever-Rideshare indicator (only the interacted coefficients are shown). In both Columns (2) and (3), the coefficient in the post period becomes insignificant for positive deviations: All the smoothing benefits load on negative deviations. The results are very similar across the two columns, showing a 19 percentage point decrease in the responsiveness of spending to income. This explains part of the reason why the Post Rideshare\(_{i,t}\) indicator was so high in Table 5—the regression was fitting a single line through a nonlinear relationship. The coefficient on Post Rideshare\(_{i,t}\) in this specification shows a 4.78 percent increase in spending in the post period, slightly higher than in the event study.

I return to my more parsimonious specification and explore some additional robustness checks. The next set of results reported in Table 7 exploit Uber’s staggered geographic entry into different markets. Because identification in this specification comes from differences across cities, the sample is restricted to include households that were in the data prior to Uber’s launch. This restriction cuts the sample size by 2/3. Major cities like San Francisco and New York are dropped from the sample since Uber launched before the data begin. To ensure that the sample is not different in any fundamental ways to the full sample, I first show the OLS estimate for this subsample in Column (1). The coefficients are broadly in line with the main sample. Rideshare drivers appear even worse at smoothing, with an elasticity of spending to income 7.41 percentage points higher than matched coworkers. The benefits of rideshare are slightly larger than the earlier OLS results, showing a 9.6 percentage point decline. In Column (2), Post Rideshare\(_{i,t}\) is instrumented with the indicator for Uber’s entry, and Column (3) adds in coworker earnings and all possible interactions to the instrument set. The results in Column (2) shows that the consumption-smoothing benefit gets approximately 2.5 percentage points larger in magnitude, while the other coefficients are unchanged. In Column (3), which includes the full instrument set, the estimated decrease in responsiveness gets very large in magnitude, -0.318. However, the standard errors, which are two-way clustered on firm and city, become 6 times larger than the OLS. The pre-period response
of spending to income given in the first row is 0.377, which is similar to the earlier IV result in Table 5. Summing the first three rows of Column (3) gives the responsiveness in the post period, 0.377+0.009-0.318=0.068. This result implies consumption insurance from main income increased by 82% after starting rideshare. For completeness, the first stage is shown in Table 8. Column (1) shows that Uber Launch \times Ever Uber is a strong predictor of rideshare driving—being in the post period increases the probability of driving by 35.8 percentage points. Column (2) shows that coworker earnings are a strong predictor of payroll earnings, with an elasticity of 0.405, very precisely estimated. In Column (4), the interaction has a coefficient of 0.223, a large effect, but imprecisely estimated. Taken together, the full instrument set is sufficiently strong. The last row of Table 7 is the Kleibergen-Paap F statistic, which is used to check for weak instruments. For the main regression in column (3) containing the full instrument set, the F-statistic is 11.79, exceeding the “rule-of-thumb” of 10. These standard errors are again two-way clustered on firm and city.

Finally, Table 9 examines whether shopping behavior may be driving any of the results. Column (2) adds leads and lags to the baseline specification. The responsiveness of spending to income declines by three percentage points but the increase in consumption smoothing is unchanged. Column (3) aggregates over two biweeks. Now, the responsiveness of spending to income is unchanged, but the increase in consumption smoothing declines by 1 percentage point. Overall, the coefficients are largely stable, suggesting that the regression is picking up something about actual consumption behavior and not changes in shopping or household inventories.

6 Model Estimation

The empirical results are qualitatively consistent with key predictions from the model in Section 2 for an exogenous decrease in costs of adjusting hours. Few, if any, estimates of the costs of intensive margin frictions on hours exist in the literature. I have argued that
rideshare entry provides a credible experiment that can be used to estimate these frictions.

In this section, I proceed with structural estimation of a tractable version of the model in Section 2. The experiment I consider is going from a world with frictions of size $\kappa_{pre}$ to $\kappa_{post} = 0$. The aim of this exercise is to get back-of-the envelope estimates of costs of adjusting hours in traditional jobs, $\kappa_{pre}$, and a sense of the magnitude of the welfare benefits from reducing these costs. The magnitude of these costs is potentially important for a wide range of economic models in labor and macroeconomics. I will structurally estimate two key parameters: the household discount factor, $\beta$, and $\kappa_{pre}$ using Simulated Method of Moments (SMM).

In addition to SMM, there are two other main methods used in the literature to solve models of this class: log-linearizing the Euler equations (Blundell, Pistaferri and Saporta-Eksten 2016) and Generalized Method of Moments (GMM). It is difficult to incorporate constraints, like the credit and hours constraints of interest here, in these alternative frameworks. Moreover, GMM performs poorly in the presence of measurement error (Carroll, 2011). My SMM procedure matches well-identified moments from my differences-in-differences research design. While alternative mechanisms like shopping or inventory behavior add measurement error to consumption and are likely to confound some moments, my robustness checks have shown that these alternative activities do appear to be first-order for the responsiveness of spending to biweekly income or the average increase in consumption in the post period. I therefore proceed with my more parsimonious model from Section 2 rather than attempting to incorporate shopping/inventory behavior into the model.

Before proceeding with estimation, I begin by delineating additional model assumptions and the calibration of the exogenous variables. I invoke a simple utility function separable in consumption and leisure that is widely used in the literature. Recall my consumption results exclude auto expenses, which are likely to be the largest non-separability for the

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17 Rideshare likely has additional costs associated, such as car initial car repairs/ cleaning. As the horizon extends, a one time fixed cost will be a very small share of the total benefits (unless it is very large, like buying a car).
group considered here. A separable utility function has computational advantages, although my framework can incorporate other classes of utility functions with non-separabilities at additional computational cost. One of the inputs into the model is the biweekly earnings process; I use a first-order Markov process estimated from the app data. After the model is estimated, I consider sensitivity to other parameterizations, before proceeding with welfare calculations.

6.1 Additional Model Assumptions

The model presented in Section 2 has no closed form solution except in special cases (e.g. quadratic utility). I consider a numerical solution. To make progress, a number of additional assumptions must first be made. Utility is assumed to be the following commonly used, separable utility function:

$$U(c_t, h_t) = \frac{c_t^{1-\rho}}{1-\rho} - \alpha \frac{h_t^{1+1/\eta}}{1+1/\eta}$$

where $\rho$ is the inverse intertemporal elasticity of substitution, $\eta$ is the labor supply elasticity, and $\alpha$ determines how households weight the disutility of work.\(^{18}\)

Since interest-rate dynamics are unremarkable over my time period of study, I assume $R_t = R$. An additional assumption that $\beta R < 1$ (“impatient” consumers) ensures that households will not accumulate unlimited assets. Households cannot borrow $(A=0)$. I assume a coefficient of relative risk aversion of 1.38, taken from (Gourinchas and Parker 2002), and a labor supply elasticity of 1.35 (the average of the estimated labor supply elasticities for Uber drivers across Angrist, Caldwell and Hall 2017 and Chen et al. 2017). $\alpha$ is chosen so that the household desires no second hours in the steady state at the main job wage.

For the earnings process for second jobs, I assume, $w_t^2 \sim N(15, 5^2)$, which is the statistical process of Uber earnings reported in Chen et al. (2017), with an adjustment to mean earnings for expenses.\(^{19}\) The next subsection explores the main earnings process.

\(^{18}\)For example, this same utility function is used to understand lifecycle labor supply in Heathcote et al. (2014) and the response of hours to credit constraints in Domeij and Floden (2006).

\(^{19}\)Chen et al. (2017) report mean earnings (before expenses) centered at $20. I subtract off 25 percent for
6.1.1 The Biweekly Earnings Process

A first-order Markov process is estimated based on the biweekly income process in the app data. In Figure 7, Panel (a), I plot the distribution of residualized earnings (removing year and household fixed effects) of biweekly pay. Earnings changes are centered at zero. The biweekly income process is very volatile: more than 41 percent of biweeks have an earnings deviation greater than 5 percent. Moreover, this distribution has high-kurtosis and “fat-tails,” as recently documented in lower frequency earnings data by Guvenen et al. (2016).

Panel (b) shows an impulse response function (IRF) for earnings changes, calculated via a local projection (Jordà, 2005):

\[
\text{Log Main Pay}_{i,t+h} = \beta^{(h)} \text{Log Main Pay}_{i,t} + \delta^{(h)} \text{Log Main Pay}_{i,t-1} + \alpha_i^{(h)} + \alpha_t^{(h)} + e_{it}^{(h)} \tag{20}
\]

where \( \text{Log Main Pay}_{i,t+h} \) is log biweekly earnings at time \( t+h \), and \( \alpha_i \) and \( \alpha_t \) are household and paydate fixed effects, respectively. The sample is restricted to earnings received every 14 days. I run this specification for \( h \) up to 13 biweeks (one quarter) after time \( t \), and plot the \( \beta^{(h)} \) coefficients in Panel (b) of Figure 7. The figure can be interpreted as an IRF. The IRF shows that high frequency income shocks appear to follow an ARMA process.

Examining the earnings process alone does not tell us whether earnings changes are coming from hours or wages. Both sources of variation have been explored in the literature. For instance, general equilibrium models with labor adjustment costs imply that wages will need to adjust by more than in a flexible model to induce a labor supply response (see Cogley and Nason, 1995). While adjustment costs may explain quarterly or even monthly variation (e.g. overtime pay), wages tend to be “sticky,” particularly in high frequency from paycheck to paycheck.\(^{20}\)

An alternative framework consistent with the high frequency the Uber fee and other expenses to arrive at a mean wage of $15.\(^{20}\)

There are obviously some important exceptions to this simplification, including tips, bonuses, commission, that likely contribute in important ways to the earnings process, and which I abstract from. Appendix A.2 explores the hours process in household survey data, showing a substantial amount of variation in earnings comes from hours.
process is long-term contracts with partial insurance (see, for instance, Lamadon 2016).

To arrive at a tractable earnings process based on the underlying data, I proceed under the following assumption: hours and overtime pay are the primary source of volatility in the main job. I discretize the biweekly earnings changes in the app data and calculate an empirical Markov transition matrix, which is reported in Appendix Table A2. I translate this into hours by assuming that at a deviation of 0, households work 80 hours (40/hours week). Above 80 hours, households are assumed to receive overtime pay at 1.5 times the wage. I estimate the average wage as the average of Median Earnings/80 in the app data.

Table 10 summarizes these assumptions and the calibrated parameters. The household discount rate, $\beta$, and the fixed costs of work, $\kappa$, remain to be estimated.

6.2 Solution Method

Given a parameterization of the model, the solution is characterized by the optimal policy functions for consumption and hours. There are many ways to solve for the policy functions via numerical methods, e.g. value function iteration, Euler equation iteration, and endogenous grid methods. I proceed by backwards induction from time $T$ using standard endogenous grid methods. As the horizon recedes, this will converge to the steady state solution under the assumptions (Deaton 1991). The difference from the standard case without hours is that now cash on hand is a function of hours as well. The cases given by Equation (11) are used to solve implicitly for the hours policy.

Once I have the solved policy functions, I consider what happens when we go from a world with frictions of size $\kappa_{\text{pre}}$ to $\kappa_{\text{post}} = 0$. I simulate the model for 1,000 agents, and match to a simple regression run on the simulated data using the variation from when rideshare turns on in a hypothetical city—the same variation used in my IV regression.21 The SMM

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21As soon as a household gets access to the new policy function, consumption will immediately jump. This is inconsistent with my empirical results, which showed a jump in consumption only upon receipt of first income. In the real world, adoption lags after Uber enters a city. This may be due to information frictions—households will take time to learn about about ridesharing, perhaps through someone in their network who also drives or after seeing an advertisement.
estimating equation is given by:

$$\min_{\theta} m(\theta) V^{-1} m(\theta)$$

(21)

where \(m(\theta) = b_k - \beta_k(\theta)\). \(b_k\) are the reduced-form estimates that I target. I will match the model to my OLS estimates from Column 1 of Table 5 and three main IV estimates: instrumenting with leave-out mean firm earnings (Column 5 of Table 5), instrumenting with Uber’s launch (Column 2 of Table 7), and the full instrument set (Column 3 of Table 7). \(\beta_k(\theta)\) are the corresponding model moments, conditional on a parameter vector, \(\theta = [\beta, \kappa]\).

The (inverse) estimated variance-covariance matrix from the reduced-form regressions is used as the weighting matrix.

### 6.2.1 Welfare

The welfare gains from reducing the fixed cost of work will generally be less than \(\kappa\) due to non-participation. In addition, the consumption gains are also not sufficient for welfare analysis, because increased labor supply in the post period decreases welfare. To answer the question, “How much would the household be ‘willing to pay’ in the pre-period to eliminate the fixed costs of a second job,” I consider a measure of consumption equivalence variation, defined as the value of \(\omega\) that solves:

$$V((1 + \omega)c^{\text{pre*}}_\text{pre}, h^{\text{pre*}}_\text{pre}) = V(c^{\text{post*}}_\text{post}, h^{\text{post*}}_\text{post})$$

(22)

where \(c^{\text{pre*}}_\text{pre}, h^{\text{pre*}}_\text{pre}, c^{\text{post*}}_\text{post}, h^{\text{post*}}_\text{post}\) are the converged (infinite-horizon) consumption and hours rules in the pre and post periods, respectively. The consumption and hours policies will depend on the distribution of constrained hour draws in the main job, the distribution of second wage draws, and the distribution of assets. Average willingness-to-pay is calculated
by aggregating over these distributions:

\[
\mathbb{E}[WTP] = \int \int \int \omega(A_{pre}; e_1; w_2) c^{pre} f(e_1) f(w_2)f(A_{pre}) de_1 dw_2 dA_{pre}
\] (23)

I assume that the distribution of hour draws for the main job has not changed over the pre and post period. While rideshare jobs were not available in the “pre-period,” I will assume, as in the main estimation, that a second job with the same wages was available, after paying the fixed cost of work. The distribution of assets will change in the pre and post-periods (the household will not need to acquire as many assets since they can now work if they receive a very low income draw). I use the pre-period asset distribution in this exercise.

6.3 Estimation Results

Estimation results are shown in Table 11. Columns (1), (3), (5) and (7) reproduce the targeted moments from earlier regressions. Column (2) shows the first set of results, matching to my OLS estimates of Column (1) of Table 5 (pre-period smoothing for ever-rideshare drivers is the summation of rows 1 and 2 of Table 5). Structural estimation can nearly perfectly match these coefficients with just the two parameters. \(\kappa_{pre}\) is estimated at $391 per biweek and the discount factor \(\beta\) is estimated to be 0.965. Willingness-to-pay for removing these large fixed costs of work, calculated as described in Section 6.2.1, are reported in Row 8 of Table 11. Willingness to pay is estimated to be 59.90 per biweek. Column (4) shows the results from matching to the IV specification instrumenting with coworker earnings from Column (5) of Table 5. Now, \(\kappa_{pre}\) is estimated at $536 per biweek and the discount factor \(\beta\) is estimated to be 0.96 and willingness to pay is estimated to be 70.90 per biweek.

Note that this is a biweekly \(\beta\), so the annualized discount factor is \(0.96^{26} = 35\) percent. While this is a considerable degree of impatience, the estimate is not far out of line with other empirical calibrations in the literature using high-frequency data. Ganong and Noel (2017) find that fitting data on UI benefit exhaustion requires 30 percent of agents be hand-
Laibson et al. (2017) use credit card data and estimate a period-ahead discount factor of 0.504 and a long-term annualized discount factor of 0.987 (so-called $\beta$-$\delta$ discounting).

Column (6) reproduces the estimated coefficients from Column 2 of Table 7, instrumenting for Uber’s launch, and Column (5) reports the corresponding estimation results. These coefficients are matched with a fixed cost of $1,269, 2 times larger, with a more reasonable discount factor, 0.992, or 81.1 percent at an annualized rate. Column (8) reproduces the estimated coefficients from Column 3 of Table 7, instrumenting with both Uber’s launch and coworkers’ income, and Column (7) reports these estimation results. Weighting by the uncertainty of the estimates matches the consumption response in the pre-period, but underestimates the increased ability to smooth consumption. The estimation sets the fixed costs of work in the pre-period very high, at over $4,000 per pay period, which has the effect of shutting off second hours in the pre-period.\footnote{The full IV-estimates can be easily matched if we assume a structural break in the distributions of main job earnings or second job earnings, or a household preference shock.}

Given the uncertainty in my IV estimates, I cannot reject equality across the IV specifications. For this reason, I proceed treating the estimates in Column (4)—the most conservative results based on IV estimates—as the baseline.

To give an idea as to the stability of these structural estimates to different parameterizations, Table 12 shows the results for a range of $\rho$ (the inverse elasticity of substitution) and $\eta$ (labor supply elasticity) values that are typically seen in the literature. The estimates for $\kappa$ range between $240$ and $1,520$ dollars. Willingness to pay is much less dispersed: between $60$ and $90$ per biweek. Again, this is because high values of the fixed cost do not necessarily map to welfare; the household can simply choose not to participate. Examining the grid of results, a number of interesting patterns emerge. First, the estimated costs are strictly increasing in $\eta$ and $\rho$. Second, estimated $\beta$’s are decreasing in $\rho$, but are relatively stable across $\eta$’s. Swanson (2012) shows that relative risk aversion for these preferences is given by: $1/(\rho^{-1} + \eta)$. Risk aversion is thus increasing in $\rho$ and decreasing in $\eta$. If a household wants to smooth consumption using assets (high $\rho$) or labor supply (high $\eta$), then it must be the
case that the fixed costs are large to generate big increases in consumption smoothing. The willingness to pay to eliminate the costs are decreasing for $\eta < 1$, but then increase as the costs rise and the household wants to smooth more.

6.3.1 Policy Functions

I plot the policy functions for consumption and hours implied by the baseline parameter estimates in Figure 8. Panel (a) shows consumption as a function of cash on hand (which is itself a function of hours) for the pre- (red) and post-periods (green). I consider two cases: a 20 percent cut in main hours (lines indexed by “o”) and steady state hours (lines indexed by “+”). The consumption policy looks similar in the steady state, but is now considerably higher for a negative deviation in total hours. In addition, the probability of being at a particular value of cash on hand will be different because households can now control hours. The distribution of cash on hand in each period is shown below the consumption policy functions. In the post period, the household is less likely to be on the hand-to-mouth portion of the consumption function where consumption is equal to income.

Panel (b) shows the hours policy function. The hours decision is very different in the pre and post periods. In the pre period, households do not participate in the second labor market for shocks in the main job (up to 20 hours) due to the high costs of taking a second job. After reducing the cost of $\kappa$, households participate in the second job when they face a drop in hours in their main job. In the low asset state (green line indexed by “o”), households will work even more for the same hours deviation.

6.3.2 Impulse Response Functions

To illustrate model dynamics, I next consider an experiment where the household receives a one-time 20-hour cut in hours in their main job from the steady state. The results of this experiment are shown in Figure 9.

The impulse response functions for the regime before flexible jobs are indexed by “o”.

45
We see that consumption falls with assets. Given the costs of participating in the second job, it is not beneficial for the household to participate. The final panel shows the Lagrange multiplier on the borrowing constraint, interpretable as the gain in marginal utility from relaxing the borrowing constraint.

The world where labor supply can be increased frictionlessly in second jobs is indexed by “+”. By comparison, consumption is far less volatile. We see that nearly all the loss in hours in the main job is compensated with the second job. The welfare losses from the borrowing constraint are roughly one-third the size for this shock to main hours.

6.3.3 Counterfactuals

Finally, I use the model to explore a number of counterfactuals that place the willingness to pay estimates in context. First, I calculate the willingness to pay to eliminate all negative shocks in the main job. Results are reported in the first row of Table 13. The household would be willing to pay 143.51 per pay period, on average, to eliminate all negative shocks, or $3,700 per year. Next, I calculate how much the household would be willing to pay to eliminate the borrowing constraint. The inability to borrow generates a welfare loss of $105.10 (Row 2). Households would be willing to pay $21.80 to increase the borrowing constraint by $100, approximately 8 percent of after-tax biweekly earnings (Row 5). This large willingness-to-pay to reduce the borrowing constraint can provide insight into why some households might undertake costly credit card debt or payday loans. Recall that eliminating the fixed cost of work was valued at $70.90 per biweek in my baseline estimates, which is 67 percent of the gains from completely eliminating the borrowing constraint. As one more point of reference, I calculate the welfare gains just from removing the bottom 25 percent of shocks. This is valued at $68.60, approximately the same as gaining access to costless second jobs.

23The model also includes positive shocks (overemployment). For small positive shocks, the household is actually better off because of the overtime premium. Large positive shocks, although rare, generate welfare losses. On net, the household would be worse off by about 2 percent if positive shocks were eliminated.
7 Conclusion

The typical worker that selects into ridesharing appears to be using a flexible job to mitigate volatility in a main job. In the period after starting rideshare, rideshare income replaces 73 percent of income losses from main payroll jobs. The link between spending and main income, which is around 1/3 in the population, declines by 82 percent in my specification exploiting the staggered geographic entry of rideshare and income movements common to all workers at the firm. When these moments are matched to a structural model with labor supply frictions, biweekly fixed costs of work are estimated at over $500. In my preferred specification, households would be willing to pay $70.90 per week or $1,800 per year, to eliminate these costs. Even though I focus on ridesharing employment, the benefits of flexibility should extend to any second job with hours flexibility and limited search and transaction costs.

This study has two important implications. The first is for the welfare costs of income fluctuations. The large fixed costs of second work estimated in this paper provide an alternative explanation for why households may not seek to increase hours when faced with “small” shocks. One interpretation has been that households are fully insured with assets/savings and highly value their leisure. This paper qualifies this statement to be that leisure is more valuable than the costs of finding additional employment.

Second, this paper provides insight on when flexible work is valuable. A recent study by Mas and Pallais (forthcoming) finds that workers prefer stability over flexibility in their job arrangements. In reality, workers often do not have complete control over their hours from week to week. When faced with volatile incomes in main jobs and credit market imperfections, flexible jobs can be valuable. When credit constrained, using labor supply instead of assets to smooth transitory shocks is a “second-best” way to smooth because of the disutility of work. However, the availability of flexible labor supply can provide substantial benefits in the presence of credit market imperfections. I estimate that the welfare gains from eliminating costly second jobs is about 2/3 of the gains from completely eliminating

47
the borrowing constraint.

One relevant question for welfare is whether the benefits estimated in this paper are simply a transfer from the incumbent sector, taxi drivers. Appendix A examines wages, hours and earnings in the taxi industry, finding no apparent impact on taxi drivers (although the value of taxi medallions has notably fallen).

A second policy concern is that work in ridesharing and related industries operates largely outside of the existing legal framework governing employment. New policies have been proposed to extend certain existing employment provisions to non-traditional employment relationships and the legal definition of an “employee” is currently being debated in the courts. To the extent that these policies limit flexibility, they could end up hurting workers using flexible work as a consumption smoothing mechanism; at the same time, work practices that gain an edge from operating outside a regulatory framework could also put workers and others at risk.

The welfare estimates from this paper depend on a variety of assumptions, one of which is the earnings process in the second job. If wages fall, because monopsonistic platforms set lower wages, or because more workers enter the sector, driving wages down, then obviously so will the benefits for workers. For the latter reason, ridesharing is likely a better smoothing mechanism for idiosyncratic, rather than aggregate shocks. As the rideshare industry and related sectors continue to grow, the policy concerns and general equilibrium implications just highlighted will likely become more relevant.

References


\[25\] See, for instance, (Harris and Krueger, 2015)

\[26\] For a discussion of ongoing litigation, see Isaac, Mike and Noam Scheiber. April 21, 2016. “Uber Settles Cases With Concessions, but Drivers Stay Freelancers,” The New York Times [Link]


_ , _, and Itay Saporta-Eksten, “Consumption Inequality and Family Labor Supply,”


_, Shachar Kariv, Matthew D. Shapiro, Dan Silverman, and Steven Tadelis, “Harnessing naturally occurring data to measure the response of spending to income,”


Hall, Jonathan D., Craig Palsson, and Joseph Price, “Is Uber a substitute or complement for public transit?,” July 2016.


Laibson, David, Peter Maxted, Andrea Repetto, and Jeremy Tobacman, “Estimation Discount Functions with Consumption Choices over the Lifecycle,” January 2017.


“Taxi and Chauffeurs (CPS)” is the weighted count of currently employed individuals with the occupation code “Taxi and Chauffeurs” (occupation code [peio1ocd] 9140) in the Current Population Survey Basic Monthly Files. “Taxi and Chauffeurs (ACS)” is the comparable statistic from the American Community Survey. The ACS occurs throughout the year, and so I assign ACS estimates to mid-year. “Active Uber Drivers” is from Hall and Krueger (2016), Figure 1. “Uber + Lyft” drivers is “Active Uber Drivers” multiplied by 1 plus the ratio of Lyft drivers that do not also drive for Uber to Uber drivers in the given month, where this ratio comes from the app data.
Figures show consumption-leisure tradeoffs within a period. In each panel, the household receives a different draw of main income. The household is assumed to start the period with no assets, an assumption made only for these figures. The budget constraint is illustrated by the thick black lines. Thin dashed curves trace out indifference curves. The thick dashed lines are the lines tangent to the indifference curve at non-participation in the second job (the reservation wage) or at the (hours,consumption) bundle satisfying the intratemporal condition after paying the fixed cost of participation.
Figure 3: Individual Income Residuals v Average Coworker Residuals

Figure shows income, residualized from year and individual fixed effects, against the average of coworker earnings, also residualized from year and individual fixed effects.

Figure 4: Event Study: Spending

(a) Gasoline Spending (§)

(b) Spending (Excl. Auto) (Log §)

Panel (a) plots the event-study coefficients for gasoline spending in dollars. Panel (b) plots the event-study coefficients from Specification 12 for log total spending, excluding gasoline and auto-repair spending. The area between the dashed vertical lines indicates the coefficients are estimated on a balanced sample. 95% confidence intervals are shown in dashed lines around the main estimates. Dependent variables are winsorized at the 1% level.
Panel (a) plots the event-study coefficients from Specification 12 for total income, including rideshare pay, in dollars. In Panel (b), the dependent variable is an indicator for having payroll income. In Panel (c), the dependent variable is payroll income in dollars. Weekly values are aggregated to the biweek, with biweekly periods numbered sequentially beginning the first week of December 2012. The area between the dashed vertical lines indicates the coefficients are estimated on a balanced sample. 95% confidence intervals are shown in dashed lines around the main estimates. Dependent variables are winsorized at the 1% level.
Panel (a) plots the event-study coefficients from Specification 12 for bank balances, in dollars. In Panel (b), the dependent variable is credit card utilization (credit card balance divided by credit limit), for cards with positive balances. In Panel (c), the dependent variable is credit card balances, in dollars. In Panel (d), the dependent variable is net balances (bank balance - credit card balance). The area between the dashed vertical lines indicates the coefficients are estimated on a balanced sample. 95% confidence intervals are shown in dashed lines around the main estimates. Dependent variables are winsorized at the 1% level.
Figure 7: Biweekly Earnings Process for Main (Non-Rideshare) Jobs

(a) Earnings Deviations from Median

(b) Impulse Response Function

Panel (a) shows the distribution of deviations of log earnings from median biweekly earnings calculated over the current year in the app data. Panel (b) shows the impulse response function for biweekly payroll income in the app data, calculated via the local projection described in the text. 95% confidence intervals based on standard errors clustered at the user level shown by dotted lines (they are very small and may not be visible). In both panels, the sample includes ever-rideshare drivers on strict biweekly paycycles and their matched coworkers. Values winsorized at the 1% level.
Policy functions use the estimated parameterization from Column (4) of Table 1.
Figure 9: Impulse Response Functions

Impulse response functions for a 20 hour shock to main earnings. The model is parameterized with the estimates from Column (3) of Table [11]
<table>
<thead>
<tr>
<th>Table 1: Descriptive Statistics - Full Sample, Weekly Values</th>
</tr>
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<tbody>
<tr>
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</tr>
<tr>
<td>Spending</td>
</tr>
<tr>
<td>SD_t</td>
</tr>
<tr>
<td>Log Spending</td>
</tr>
<tr>
<td>SD_t</td>
</tr>
<tr>
<td>Income</td>
</tr>
<tr>
<td>Payroll Income</td>
</tr>
<tr>
<td>Bank Balance</td>
</tr>
<tr>
<td>CC Balance</td>
</tr>
<tr>
<td>CC Utilization Rate</td>
</tr>
<tr>
<td>Net Balance</td>
</tr>
<tr>
<td>Northeast</td>
</tr>
<tr>
<td>Midwest</td>
</tr>
<tr>
<td>South</td>
</tr>
<tr>
<td>West, Excl. CA</td>
</tr>
<tr>
<td>CA</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

Notes: Column (1) and (2) show average and median weekly values, pre- and post- starting rideshare, respectively, for the full sample of ever-rideshare drivers satisfying the sample selection criteria discussed in the text. Columns (2) and (3) shows the average and median weekly values, pre- and post-starting rideshare, respectively, for the subsample of biweekly earners with no break in employment 6 weeks prior to starting rideshare and 4 weeks after starting rideshare and with identifiable main employers. SD_t refers to the household’s time-series standard deviation of the variable from one row above. All dollar values and log dollar values are winsorized at the 1% level.
Table 2: Descriptive Statistics - Biweekly Earners, Biweekly Values

<table>
<thead>
<tr>
<th></th>
<th>(1) Biweekly Subsample-Pre</th>
<th></th>
<th>(2) Biweekly Subsample-Post</th>
<th></th>
<th>(3) Control Coworkers</th>
</tr>
</thead>
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<td>Mean</td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
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<td>Spending</td>
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<td>2123.82</td>
<td>2744.65</td>
<td>2271.38</td>
<td>2456.40</td>
</tr>
<tr>
<td>SDt</td>
<td>1459.03</td>
<td>1065.33</td>
<td>1482.30</td>
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</tr>
<tr>
<td>Log Spending</td>
<td>7.54</td>
<td>7.52</td>
<td>7.60</td>
<td>7.60</td>
<td>7.37</td>
</tr>
<tr>
<td>SDt</td>
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<td>0.49</td>
<td>0.54</td>
<td>0.50</td>
<td>0.58</td>
</tr>
<tr>
<td>Income</td>
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<td>2234.05</td>
<td>2844.68</td>
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<td>Log Income</td>
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<tr>
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<td>0.49</td>
<td>0.47</td>
<td>0.49</td>
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<tr>
<td>Payroll Income</td>
<td>1321.55</td>
<td>1192.19</td>
<td>1355.74</td>
<td>1217.65</td>
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<td>Log Payroll Income</td>
<td>7.01</td>
<td>7.05</td>
<td>7.03</td>
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<td>7.01</td>
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<tr>
<td>SDt</td>
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<td>0.19</td>
<td>0.21</td>
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<td>Bank Balance</td>
<td>3458.97</td>
<td>887.77</td>
<td>3803.53</td>
<td>921.97</td>
<td>5538.64</td>
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<td>CC Balance</td>
<td>5009.36</td>
<td>2662.98</td>
<td>6041.40</td>
<td>3311.69</td>
<td>4469.93</td>
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<td>CC Utilization Rate</td>
<td>0.49</td>
<td>0.46</td>
<td>0.47</td>
<td>0.43</td>
<td>0.40</td>
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<tr>
<td>Net Balance</td>
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<td>-1234.56</td>
<td>-1858.37</td>
<td>-1757.76</td>
<td>1987.03</td>
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<td>0.14</td>
<td>0.14</td>
<td>0.13</td>
<td>0.14</td>
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<td>Midwest</td>
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<td>0.11</td>
<td>0.12</td>
<td>0.11</td>
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<tr>
<td>South</td>
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<td>0.41</td>
<td>0.41</td>
<td>0.39</td>
<td>0.41</td>
</tr>
<tr>
<td>West, Excl. CA</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.12</td>
<td>0.10</td>
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<tr>
<td>CA</td>
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<td>0.22</td>
<td>0.22</td>
<td>0.15</td>
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<tr>
<td>Observations</td>
<td>2217</td>
<td>2217</td>
<td>468365</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Columns (1) and (2) show the average and median biweekly values, pre- and post- starting rideshare, respectively, for the subsample of biweekly earners with no break in employment 6 weeks prior to starting rideshare and 4 weeks after starting rideshare and with identifiable main employers. Spending is calculated in the 14 days following receipt of income, while asset values are for the day prior to receiving income. Column (3) shows results for matched coworkers at the same payroll employers ever-rideshare drivers work at in the six months prior to starting rideshare. SDt refers to the household’s time-series standard deviation of the variable from one row above. All dollar values and log dollar values are winsorized at the 1% level.
Table 3: Event Study Results, By Spending Category

<table>
<thead>
<tr>
<th>Category</th>
<th>6 weeks pre</th>
<th>1 week post</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>-14.91</td>
<td>74.42***</td>
</tr>
<tr>
<td></td>
<td>(16.39)</td>
<td>(17.31)</td>
</tr>
<tr>
<td>Gasoline</td>
<td>-1.144**</td>
<td>19.08***</td>
</tr>
<tr>
<td></td>
<td>(0.560)</td>
<td>(0.617)</td>
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<tr>
<td>Service &amp; Parts</td>
<td>-5.900***</td>
<td>0.101</td>
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<tr>
<td></td>
<td>(1.505)</td>
<td>(1.765)</td>
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<tr>
<td>Fast Food</td>
<td>0.484</td>
<td>2.763***</td>
</tr>
<tr>
<td></td>
<td>(0.295)</td>
<td>(0.296)</td>
</tr>
<tr>
<td>Groceries</td>
<td>0.973</td>
<td>3.860***</td>
</tr>
<tr>
<td></td>
<td>(1.018)</td>
<td>(1.050)</td>
</tr>
<tr>
<td>Restaurants/Bars</td>
<td>0.425</td>
<td>5.241***</td>
</tr>
<tr>
<td></td>
<td>(0.880)</td>
<td>(0.907)</td>
</tr>
<tr>
<td>Personal Care/Services</td>
<td>-1.562</td>
<td>5.214</td>
</tr>
<tr>
<td></td>
<td>(2.921)</td>
<td>(3.301)</td>
</tr>
<tr>
<td>Clothing</td>
<td>2.669**</td>
<td>4.349***</td>
</tr>
<tr>
<td></td>
<td>(1.042)</td>
<td>(1.111)</td>
</tr>
<tr>
<td>Electronics</td>
<td>0.412</td>
<td>3.444*</td>
</tr>
<tr>
<td></td>
<td>(1.836)</td>
<td>(1.897)</td>
</tr>
</tbody>
</table>

The table shows coefficients from the main event study where the dependent variable is indicated in the rows. Units are given in dollars. The time-frame of aggregate is week. Results are relative to pay periods 2 weeks before starting rideshare. Standard errors clustered on individual in parentheses. * p<0.1, ** p<0.05, *** p<0.01
<table>
<thead>
<tr>
<th></th>
<th>(1) Spending</th>
<th>(2) Total Income</th>
<th>(3) Payroll Income</th>
<th>(4) Bank Balance</th>
<th>(5) CC Balance</th>
<th>(6) Net Balance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre, 90+ days</td>
<td>0.00546</td>
<td>0.0220**</td>
<td>0.0257***</td>
<td>1.436**</td>
<td>-0.818</td>
<td>2.205**</td>
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<tr>
<td></td>
<td>(0.0110)</td>
<td>(0.0103)</td>
<td>(0.00580)</td>
<td>(0.711)</td>
<td>(0.605)</td>
<td>(1.025)</td>
</tr>
<tr>
<td>Pre, 31-90 days</td>
<td>0.00749</td>
<td>0.0205**</td>
<td>0.0161***</td>
<td>0.668</td>
<td>-0.0938</td>
<td>0.557</td>
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<td></td>
<td>(0.00962)</td>
<td>(0.00913)</td>
<td>(0.00434)</td>
<td>(0.613)</td>
<td>(0.348)</td>
<td>(0.812)</td>
</tr>
<tr>
<td>Post, 0-30 days</td>
<td>0.0395***</td>
<td>0.103***</td>
<td>-0.00247</td>
<td>-0.609</td>
<td>0.409*</td>
<td>-1.434**</td>
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<tr>
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<td>(0.00970)</td>
<td>(0.00444)</td>
<td>(0.459)</td>
<td>(0.240)</td>
<td>(0.656)</td>
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<tr>
<td>Post, 31-90 days</td>
<td>0.0359***</td>
<td>0.0750***</td>
<td>-0.0172***</td>
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<td>-0.0575</td>
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<td>(0.0112)</td>
<td>(0.0107)</td>
<td>(0.00572)</td>
<td>(0.679)</td>
<td>(0.387)</td>
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<tr>
<td>Post, 90+ days</td>
<td>0.0249**</td>
<td>0.0494***</td>
<td>-0.0174***</td>
<td>-0.155</td>
<td>0.140</td>
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<tr>
<td></td>
<td>(0.0104)</td>
<td>(0.0101)</td>
<td>(0.00654)</td>
<td>(0.852)</td>
<td>(0.560)</td>
<td>(1.286)</td>
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</table>

The table shows coefficients from an event study specification grouping together pay periods as indicated in the rows. Results are relative to pay periods ending 1-30 days before starting rideshare. Standard errors clustered on user in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Table 5: Results: Consumption Smoothing - Baseline

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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tr>
<td>Log Pay</td>
<td>0.304***</td>
<td>0.304***</td>
<td>0.311***</td>
<td>0.292***</td>
<td>0.373***</td>
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<tr>
<td></td>
<td>(0.00366)</td>
<td>(0.00361)</td>
<td>(0.00341)</td>
<td>(0.00365)</td>
<td>(0.0185)</td>
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<tr>
<td>Log Pay × Ever Rideshare</td>
<td>0.0392**</td>
<td>0.0385*</td>
<td></td>
<td>0.0385*</td>
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<tr>
<td></td>
<td>(0.0198)</td>
<td>(0.0199)</td>
<td></td>
<td>(0.0199)</td>
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</tr>
<tr>
<td>Post Rideshare × Log Pay</td>
<td>-0.0677***</td>
<td>-0.0573***</td>
<td>-0.0593***</td>
<td>-0.0659***</td>
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<td>Post Rideshare</td>
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<td>X</td>
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<td>User FE</td>
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<td>Year FE</td>
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<td>2217</td>
<td>2217</td>
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<td>Control N</td>
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<td>OLS</td>
<td>OLS</td>
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<td>IV</td>
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<td>K/P F-stat</td>
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<td></td>
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<td>104.22</td>
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</table>

The table shows coefficients from Specification (14) in the text. Weights are discussed in Section (B.2). Standard errors in parentheses. In Columns (1)-(4), standard errors are clustered on user. In Column (5), standard errors are clustered on firm. * p<0.1, ** p<0.05, *** p<0.01
Table 6: Results: Consumption Smoothing - Response to Negative Deviations

<table>
<thead>
<tr>
<th></th>
<th>(1) Log Spending</th>
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<th>(3) Log Spending</th>
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</thead>
<tbody>
<tr>
<td>Log Pay</td>
<td>0.311***</td>
<td>0.317***</td>
<td>0.351***</td>
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<td></td>
<td>(0.00341)</td>
<td>(0.00437)</td>
<td>(0.0191)</td>
</tr>
<tr>
<td>Log Pay × Neg</td>
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<td>-0.0364***</td>
<td>-0.0729***</td>
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<tr>
<td></td>
<td></td>
<td>(0.00434)</td>
<td>(0.0218)</td>
</tr>
<tr>
<td>Post Rideshare × Log Pay</td>
<td>-0.0593***</td>
<td>0.0299</td>
<td>0.0304</td>
</tr>
<tr>
<td></td>
<td>(0.0110)</td>
<td>(0.0416)</td>
<td>(0.0411)</td>
</tr>
<tr>
<td>Post Rideshare × Log Pay × Neg</td>
<td>-0.193***</td>
<td>-0.191***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0613)</td>
<td>(0.0619)</td>
</tr>
<tr>
<td>Post Rideshare</td>
<td>0.477***</td>
<td>0.475***</td>
<td>0.479***</td>
</tr>
<tr>
<td></td>
<td>(0.0784)</td>
<td>(0.0106)</td>
<td>(0.0106)</td>
</tr>
<tr>
<td>Neg</td>
<td>-0.0138***</td>
<td>-0.0122***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00133)</td>
<td>(0.00400)</td>
<td></td>
</tr>
<tr>
<td>Neg × Post</td>
<td>-0.00728</td>
<td>-0.00901</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0133)</td>
<td>(0.0134)</td>
<td></td>
</tr>
<tr>
<td>×EverUber == 0</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NxT</td>
<td>3064697</td>
<td>3064697</td>
<td>3064697</td>
</tr>
<tr>
<td>Rideshare N</td>
<td>2217</td>
<td>2217</td>
<td>2217</td>
</tr>
<tr>
<td>Control N</td>
<td>64910</td>
<td>64910</td>
<td>64910</td>
</tr>
</tbody>
</table>

The table shows coefficients from Specification (15) in the text. Column (1) is the result from Column (3) of Table 5. Column (2) uses the control group for identification of the pre-period responses, while column (3) interacts all the coefficients shown in the table with an Ever-Rideshare indicator (only the interacted coefficients are shown). Bootstrapped standard errors clustered on user in parentheses. See text for more details. * p<0.1, ** p<0.05, *** p<0.01
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Spending</td>
<td>Log Spending</td>
<td>Log Spending</td>
</tr>
<tr>
<td>Log Pay</td>
<td>0.316***</td>
<td>0.316***</td>
<td>0.377***</td>
</tr>
<tr>
<td></td>
<td>(0.00431)</td>
<td>(0.00432)</td>
<td>(0.0172)</td>
</tr>
<tr>
<td>Log Pay × Ever Rideshare</td>
<td>0.0741**</td>
<td>0.0795**</td>
<td>0.00879</td>
</tr>
<tr>
<td></td>
<td>(0.0300)</td>
<td>(0.0379)</td>
<td>(0.0791)</td>
</tr>
<tr>
<td>StartRideshare × Log Pay</td>
<td>-0.0963***</td>
<td>-0.121*</td>
<td>-0.318**</td>
</tr>
<tr>
<td></td>
<td>(0.0190)</td>
<td>(0.0707)</td>
<td>(0.123)</td>
</tr>
<tr>
<td>StartRideshare</td>
<td>0.754***</td>
<td>0.968*</td>
<td>2.368***</td>
</tr>
<tr>
<td></td>
<td>(0.136)</td>
<td>(0.511)</td>
<td>(0.868)</td>
</tr>
<tr>
<td>User FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>NxT</td>
<td>2257372</td>
<td>2257372</td>
<td>2257372</td>
</tr>
<tr>
<td>Rideshare N</td>
<td>620</td>
<td>620</td>
<td>620</td>
</tr>
<tr>
<td>Control N</td>
<td>41711</td>
<td>41711</td>
<td>41711</td>
</tr>
<tr>
<td>IV</td>
<td>OLS</td>
<td>IV</td>
<td>IV</td>
</tr>
<tr>
<td>K-P F-Stat</td>
<td>.</td>
<td>201.99</td>
<td>11.79</td>
</tr>
</tbody>
</table>

The table shows coefficients from a restricted sample in the data before and after Uber’s launch in a city. Column (2) is instrumented with Uber’s launch into the city. Column (3) is instrumented with both Uber’s launch and coworker earnings. Standard errors in parentheses. In Column (1), standard errors are clustered on user. In Column (2), standard errors are clustered on city. In Column (3), standard errors are two-way clustered on city and firm. * p<0.1, ** p<0.05, *** p<0.01
Table 8: Instrumenting Uber’s Launch - First Stage

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Post Log</td>
<td>Main Pay</td>
<td>Log Main</td>
<td>Main Pay</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Pay × Ever Rideshare</td>
<td></td>
</tr>
<tr>
<td>Uber Launch</td>
<td>-0.00129***</td>
<td>-0.0230</td>
<td>0.000203**</td>
<td>-0.00914***</td>
</tr>
<tr>
<td></td>
<td>(0.000485)</td>
<td>(0.0362)</td>
<td>(0.000139)</td>
<td>(0.00346)</td>
</tr>
<tr>
<td>Uber Launch × Ever Rideshare</td>
<td>0.358**</td>
<td>-0.243</td>
<td>-0.253</td>
<td>1.015</td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.197)</td>
<td>(0.194)</td>
<td>(1.313)</td>
</tr>
<tr>
<td>Coworker Earnings</td>
<td>-0.000558***</td>
<td>0.405***</td>
<td>0.000000117</td>
<td>-0.00396***</td>
</tr>
<tr>
<td></td>
<td>(0.0000764)</td>
<td>(0.0283)</td>
<td>(0.0000194)</td>
<td>(0.000538)</td>
</tr>
<tr>
<td>Coworker Earnings × Ever Rideshare</td>
<td>0.0636***</td>
<td>-0.0976</td>
<td>0.309***</td>
<td>0.374**</td>
</tr>
<tr>
<td></td>
<td>(0.0222)</td>
<td>(0.0795)</td>
<td>(0.0962)</td>
<td>(0.155)</td>
</tr>
<tr>
<td>Coworker Earnings × Uber Launch</td>
<td>-0.000264***</td>
<td>0.00461</td>
<td>-0.00000180*</td>
<td>-0.00188***</td>
</tr>
<tr>
<td></td>
<td>(0.0000640)</td>
<td>(0.00505)</td>
<td>(0.0000950)</td>
<td>(0.000457)</td>
</tr>
<tr>
<td>Coworker Earnings × Uber Launch × Ever Rideshare</td>
<td>0.00144</td>
<td>0.0323</td>
<td>0.0375</td>
<td>0.223</td>
</tr>
<tr>
<td></td>
<td>(0.0229)</td>
<td>(0.0275)</td>
<td>(0.0271)</td>
<td>(0.160)</td>
</tr>
<tr>
<td>User FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>NxT</td>
<td>2257372</td>
<td>2257372</td>
<td>2257372</td>
<td>2257372</td>
</tr>
<tr>
<td>Rideshare N</td>
<td>620</td>
<td>620</td>
<td>620</td>
<td>620</td>
</tr>
<tr>
<td>Control N</td>
<td>41711</td>
<td>41711</td>
<td>41711</td>
<td>41711</td>
</tr>
</tbody>
</table>

The table shows coefficients from Specification (19) in the text. Standard errors two-way clustered on city and firm in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Table 9: Robustness to Shopping Behavior

<table>
<thead>
<tr>
<th></th>
<th>(1) Log Spending</th>
<th>(2) Log Spending</th>
<th>(3) Log Spending</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Main Pay</td>
<td>0.311***</td>
<td>0.284***</td>
<td>0.321***</td>
</tr>
<tr>
<td></td>
<td>(0.00341)</td>
<td>(0.00305)</td>
<td>(0.00469)</td>
</tr>
<tr>
<td>StartRideshare</td>
<td>0.477***</td>
<td>0.457***</td>
<td>0.413***</td>
</tr>
<tr>
<td></td>
<td>(0.0784)</td>
<td>(0.0795)</td>
<td>(0.107)</td>
</tr>
<tr>
<td>StartRideshare × Log Pay</td>
<td>-0.0593***</td>
<td>-0.0581***</td>
<td>-0.0478***</td>
</tr>
<tr>
<td></td>
<td>(0.0110)</td>
<td>(0.0112)</td>
<td>(0.0137)</td>
</tr>
<tr>
<td>L1 Log Main Pay</td>
<td>0.0552***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00229)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1 Post × L1 Log Main Pay</td>
<td>0.0136</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0139)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F1 Log Main Pay</td>
<td>0.0338***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00243)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F1 Post × F1 Log Main Pay</td>
<td>-0.0128</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0139)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregation</td>
<td>Biweek</td>
<td>Biweek</td>
<td>2 Biweeks</td>
</tr>
<tr>
<td>User FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Paydate FE</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>NxT</td>
<td>3064697</td>
<td>2653300</td>
<td>1025638</td>
</tr>
<tr>
<td>Rideshare N</td>
<td>2217</td>
<td>2217</td>
<td>1995</td>
</tr>
<tr>
<td>Control N</td>
<td>64910</td>
<td>63710</td>
<td>54472</td>
</tr>
</tbody>
</table>

Column (2) includes leads and lags in the main specification, and Column (3) aggregates Specification (14) over two biweeks. Standard errors clustered on user in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table 10: Exogenous Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>$80^{-1/\eta w_1 c^{-\rho}}$</td>
<td>$\bar{h} = 80$</td>
</tr>
<tr>
<td>$\rho$</td>
<td>1.38</td>
<td>$\text{Gourinchas and Parker, 2002}$</td>
</tr>
<tr>
<td>$\eta$</td>
<td>1.35</td>
<td>$\text{Chen et al., 2017}$</td>
</tr>
<tr>
<td>$R_t = R$</td>
<td>$(1.001)^{1/26}$</td>
<td>Biweekly Calibration</td>
</tr>
<tr>
<td>$w_1$</td>
<td>$15.53$</td>
<td>App Data: Average($\rho 50_0_0_0_{Earnings}/80$)</td>
</tr>
<tr>
<td>$F(w_2)$</td>
<td>$\sim \mathcal{N}(15, 3)$</td>
<td>Chen et al. (2017).</td>
</tr>
<tr>
<td>$F(h_1)$</td>
<td>Simulated Markov chain</td>
<td>- estimated costs</td>
</tr>
</tbody>
</table>

App Data.
Table 11: Model Estimation Results

<table>
<thead>
<tr>
<th></th>
<th>(1) Target</th>
<th>(1) Model</th>
<th>(2) Target</th>
<th>(2) Model</th>
<th>(3) Target</th>
<th>(3) Model</th>
<th>(4) Target</th>
<th>(4) Model</th>
<th>(5) Target</th>
<th>(5) Model</th>
<th>(6) Target</th>
<th>(6) Model</th>
<th>(7) Target</th>
<th>(7) Model</th>
<th>(8) Target</th>
<th>(8) Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>LogPay Log Pay × Post Rideshare Post Rideshare</td>
<td>0.3432 0.3431</td>
<td>0.3730 0.3730</td>
<td>0.3162 0.3162</td>
<td>0.3769 0.3929</td>
<td>-0.0677 -0.0704</td>
<td>-0.0908 -0.0920</td>
<td>-0.1211 -0.1231</td>
<td>-0.3183 -0.2061</td>
<td>0.5380 0.5380</td>
<td>0.6980 0.6981</td>
<td>0.9681 0.9338</td>
<td>2.3677 1.5329</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Cost of Work, ( \kappa_{pre} ) (S.E.) Discount Factor, ( \beta ) (S.E.) WTP</td>
<td>- 390.9 - 390.9 (7.59) - 965 (0.0002) - 59.91</td>
<td>- 536.0 - 536.0 (3.1) - 9604 (0.0005) - 70.90</td>
<td>- 1,2698.9 - 1,2698.9 (1.1) - 9923 (0.0005) - 147.31</td>
<td>- 4,554.8 - 4,554.8 (38.3) - 0.9935 - 0.9935 (0.0084) - 188.80</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Columns (1), (3), (5) and (7) are targeted moments, and Columns (2), (4), (6) and (8) are estimation results. Standard errors in parentheses based on numerical Jacobians.
Table 12: Estimation Results for Range of Alternative Parameter Values

<table>
<thead>
<tr>
<th>η</th>
<th>κ_{pre}</th>
<th>β</th>
<th>WTP</th>
<th>κ_{pre}</th>
<th>β</th>
<th>WTP</th>
<th>κ_{pre}</th>
<th>β</th>
<th>WTP</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>243.61</td>
<td>0.9740</td>
<td>87.37</td>
<td>310.97</td>
<td>0.9750</td>
<td>84.03</td>
<td>481.35</td>
<td>0.9760</td>
<td>88.52</td>
</tr>
<tr>
<td>1</td>
<td>340.06</td>
<td>0.9531</td>
<td>79.85</td>
<td>449.67</td>
<td>0.9545</td>
<td>69.66</td>
<td>730.59</td>
<td>0.9560</td>
<td>74.22</td>
</tr>
<tr>
<td>1.5</td>
<td>368.67</td>
<td>0.9336</td>
<td>72.30</td>
<td>537.97</td>
<td>0.936</td>
<td>62.6</td>
<td>945.40</td>
<td>0.9380</td>
<td>68.16</td>
</tr>
<tr>
<td>2</td>
<td>650.86</td>
<td>0.9762</td>
<td>80.02</td>
<td>1,151.68</td>
<td>0.9564</td>
<td>85.19</td>
<td>1,524.47</td>
<td>0.9400</td>
<td>80.02</td>
</tr>
</tbody>
</table>

The table shows the structural estimates matching to the coefficients from the IV specification reproduced in Column (4) of Table 11 for the given η and ρ indicated in the table.

Table 13: Counterfactuals

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>WTP ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eliminating All Negative Shocks</td>
<td>143.51</td>
</tr>
<tr>
<td>Eliminating Borrowing Constraint</td>
<td>105.10</td>
</tr>
<tr>
<td><strong>Eliminating Fixed Costs of Work</strong></td>
<td><strong>70.90</strong></td>
</tr>
<tr>
<td>Eliminating Extreme Negative Shocks (Bottom 20%)</td>
<td>68.60</td>
</tr>
<tr>
<td>Increasing borrowing constraint by $100</td>
<td>21.80</td>
</tr>
</tbody>
</table>

Counterfactuals are for the estimated parameterization from Column (4) of Table 11.
A Supporting Evidence from Household Surveys

A.1 Evidence on the Taxi and Chauffeur Industry

Previous work measuring non-traditional work arrangements has highlighted that contingent workers are not well-captured in the major U.S. survey datasets (Katz and Krueger, 2016), although this work has not focused on ride-share drivers specifically. Figure 1 shows the number of workers reporting “Taxi and Chauffeur” as their main occupation in the CPS. In 2016, these workers represented 0.3 percent of the workforce, up by approximately 100,000 workers since 2012. While this increase is not large enough to be consistent with the growth from ridesharing, it is possible that it does capture at least part of the rise in ridesharing.

However, digging closer into the composition of this rise suggests otherwise. Figure A1 shows that none of the rise comes from self-employed or dual job holders, which is where we would expect rideshare jobs to show up.

Figure 1 showed that there are equal number of rideshare workers as there are traditional taxi workers by 2016. On an hours-adjusted basis, however, traditional taxis still have the edge since many are working full-time. Nevertheless, this is a large supply increase in the transportation sector. Whether this has had an impact on incumbent workers is an important consideration for policy as well as economic modeling. While it appears to be the case that traditional surveys like the CPS do not capture gig economy income, the traditional taxi sector should be well-represented. I next use the CPS to examine total earnings, wages and hours in the “Taxi and Chauffeur” sector. Time series for these variables are plotted in Figure A2.

As shown in the solid lines in the figure, average wages, hours and earnings are completely flat in the taxi sector. In a related analysis, Berger, Chen and Frey (2017) examine employment and annual earnings of “Taxi and Chauffeurs” in ACS data using a triple-difference research design comparing outcomes pre- and post- Uber’s launch, relative to outcomes for bus and truck drivers. They find no effects in their most robust specifications controlling
for time trends. Their paper uses different event dates—the launch of Uber Black, not Uber X—and of course the ACS has only low frequency (annual) variation. Unfortunately, sample sizes in the CPS monthly files are too small to exploit cross-sectional variation (the median CBSA has just 3 taxi drivers per quarter in a MORG sample). Figure A2 shows nominal values for wages and earnings; we might be concerned that the counterfactual values would have increased over this period. I follow Berger, Chen and Frey (2017) and compare taxi drivers to bus and truck drivers. The time-series for these groups are shown in dashed lines, and look very similar to taxi drivers. This suggests that the increase in supply has largely been accommodated by increased demand for transportation services.27

A.2 Evidence on the Hours Process

The CPS provides evidence on hours at the monthly level. The CPS has a number of limitations: for instance, it only records rounded hours and there is likely significant recall error. Even with these limitations, there is a surprising amount of volatility in hours in any week. In Figure A3 I plot usual weekly hours, and the deviation of hours worked last week from usual weekly hours. 6 percent of households in the sample report hours usually vary, and so this deviation cannot be calculated. In addition, 20 percent of households on any given month report not being within 5 percent of usual hours, a substantial amount of hours volatility.

B Construction of Main Sample

Sources of income (and spending) are not pre-categorized or organized in the app data in the same manner as traditional survey or other datasets. Instead, we see only rows with raw transaction strings and amounts. This appendix describes how I identify rideshare drivers, how I measure consumption spending and household balance sheets, and how I construct a

27 The value of taxi medallions has declined. Since this decline does not show up in wages for taxi drivers, one interpretation is that taxi drivers themselves are not the residual claimants on the rents.
“control group” of coworkers.

B.1 Classification of Transactions Using Machine Learning

The app data are in the form of raw transaction strings. This is an important difference compared with consumption survey data like the CEX, which come pre-categorized into universal classification codes (UCC), or AC Nielsen data, where UPCs which can be easily aggregated into categories of goods. In this section, I describe how I use information in the transaction strings to categorize spending into different categories of goods. Gelman et al. (2016) use a binary machine learning (ML) model to categorize spending into “gasoline” and “not gasoline.” I extend the binary ML model to multiple classes of goods.

The ML procedure requires both a “training” data set—data actually used to fit a classification model—and a “testing” data set to evaluate the out of sample performance of the model. Two account providers in the app data report merchant category codes (MCCs) in their transaction strings. MCCs are four digit codes used by credit card companies to classify spending and are also recognized by the U.S. Internal Revenue Service for tax reporting purposes. I manually classify the many MCC codes into the following 10 categories: gas & fuel, fast food, restaurants/alcohol/bars, groceries, auto service & parts, electronics & software, clothing, personal care/services, travel spending, and all other spending. These two accounts with MCC codes represent about 3% of all app transactions.

I use the larger of the two account providers with MCC codes as the training data set, and test the performance of the model on the smaller account. I explicitly set aside the second account provider as the training data set because transaction strings, which we will feed into the model to classify the data, can differ across account providers. Therefore, if we train on data from the two accounts, we may fit our two cards extremely well, but we may have a poor “out of sample” fit of our model.

The model I use is a random forest classifier, which fits a number of separate decision trees to bootstrapped samples of the data; the final decision rule is the majority rule over the
models. A decision tree is a series of classification rules that ultimately lead to a classification of a purchase. The rules, determined by the algorithm, minimize the decrease in accuracy when a particular model “feature” is removed. The features used to train the model are the transaction values (rounded to the nearest 50 cents) and a “bag of words”—individual words that appear in the transaction strings.

Two summary statistics commonly used to assess the fit of a multiclass model are “recall” and “precision,” which are defined as follows:

\[
\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negatives}} \\
\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positives}}
\]  

These two summary statistics of model fit for each category of spending are shown in Figure A4.

My ML model is able to predict gasoline spending and fast food spending particularly well, with around 90 percent recall and precision. Restaurant spending, all other groceries, and service and parts, have recall of around 75 percent and precision of around 70 percent. Electronics, clothing and services, in particular, are less well-predicted by the model, likely because of the larger variety of transaction strings associated with spending in these categories.

### B.1.1 Rideshare Income

I search transaction strings in the app data associated with rideshare income. Rideshare income is paid weekly and on the same day, which is one way to distinguish it from traditional employees at a firm, who are typically paid on a biweekly schedule. In practice, since many rideshare drivers do not work every week, my sample keeps households with a modal gap between rideshare paychecks of 7 days.

As we move later in the sample, some drivers switch to “instant pay.” I modify the restriction so that the modal gap is for pay received on paydays with everyone else, which could be satisfied if the driver switched...
this criteria in the app data.

Knowing the timing of signing up for Uber is slightly complicated. Before 2016, Uber would first verify a new account by making a $0.01 deposit. This indicates that the user has signed up for Uber. Interestingly, there can be large gaps between account verification and first rideshare earnings. Appendix figure A9 shows the distribution of this gap. I consider a household as starting Uber the week before at least $1 of earnings are observed (since income is lagged 1 week from first working). Figure A5 compares the number of ever-rideshare drivers in the app data to data from Uber reported in Hall and Krueger (2016). Comparing the two series, the app contains approximately 1-2 percent of ever-drivers and entry follows a similar growth trend.

B.1.2 Consumption and Assets

For the baseline sample, I calculate total spending and average balances of bank accounts and credit cards over the calendar week (Sunday-Saturday). The app data have a large right tail for consumption and asset values. To ensure outliers are not driving results, all values are winsorized at the 1 percent level.

I construct a second subsample of rideshare drivers and matched coworkers with regular biweekly earnings. One biweekly paycheck is defined as being paid 14 days ago and being paid 14 days from now (therefore, three paychecks in a row must be observed).29 Biweekly earnings are the most common type of earnings process in the United States. While I could also aggregate the data to monthly level to capture weekly and monthly earners, this would cut the number of time-series observations in half; given that the time-series is already rather short (whereas the number of observations is relatively large) this is undesirable. Moreover, if most workers are paid biweekly, this is the closest to the actual decision-making time frame of the household. Households need to make consumption and asset decisions to get them through until the next paycheck.

29In implementation, I look for income over the window 13-16 days after last income.

from a regular payment scheme earlier in the sample.
In some cases, I observe payrolls from multiple employers in an account. This could be because the household has dual earners or from multijob holding; unfortunately, I am unable to separately differentiate these in the app data. If there are multiple employers, I first sort each employer by average log payroll amount. The biweekly pay series with the highest average log pay is considered the main employer from its first to its last observed receipt. Figure A6 provides a hypothetical example of an individual with multiple observed income streams. In this example, my algorithm treats the series highlighted in green as the primary employer from January 26, 2017 through March 9, 2017. There is a break between the start of a new job on March 30, 2017, and this new job then becomes the primary employer. The period from March 16, 2017 through March 23, 2017 will be dropped. In addition, this hypothetical household has weekly income from another source, highlighted in orange. “Total” payroll income over the period January 26, 2017 through February 2, 2017 will be $3,000 ($2,000+$500+$500).

The timing of consumption and assets I construct is illustrated in Figure A7. I measure spending over the 14 days following paycheck receipt, assuming that this consumption decision is made following the receipt of income and starting period assets. In the typical U.S. paycycle income received at date $t$ reflects hours worked in the previous two weeks, usually with a lag of one week in between. Therefore, since the paycycle ended a week earlier, income should largely be known with certainty at the close of the paycycle. Nevertheless, I find spending is most responsive in the two weeks after receipt of the income. This suggests credit constraints, inattention, or complexity limit the full understanding of arriving income. It is also possible that people time their consumption with their income for behavioral reasons.

For the subsample of biweekly earners, I calculate measures of the household balance sheet the day before payroll income is received, which is consistent with the theoretical literature on consumption, as in Kaplan and Violante (2014).
B.1.3 Control Group

I next identify a group of non-rideshare drivers so that I can isolate common shocks and trends. While we do not observe demographics in the app data, I do observe sources of non-rideshare income. I use this information to construct a control group of other households in the data who receive income from the same payroll employer. In particular, I restrict to a common set of employers shared with rideshare drivers in the six months predating their starting rideshare.

As in Baker (forthcoming), Ganong and Noel (2017), and Gelman et al. (2014), I identify payroll income as income containing transaction strings like “payroll” or “salary.” These transaction strings are then processed using an algorithm to extract the name of the employer. Using this information, I can identify coworkers at the same firm. In most cases, only the name of the firm can be extracted, not the establishment.

B.1.4 Estimation Sample

To construct the final sample used in estimation, I restrict to ever-rideshare drivers in the sample at least 6 weeks before I observe the first rideshare income and staying in the sample for at least 4 weeks afterwards. This assures that the pre- and post- period are being estimated off of the same households. It is also necessary to have a longer lead time due to the nature of gig-economy employment: this work tends to be highly variable from week to week. Even if no rideshare economy is immediately observed once a household enters the sample, it’s possible the household is just not working that week. Restricting the lead time to at least 6 weeks in the sample before rideshare income is first observed deals with this issue.

B.2 Weighting Control Group to Balance Covariates

The descriptive statistics in Section 3.1 showed that rideshare drivers and their matched coworkers differ in levels of income and assets. While time-invariant level differences can
be handled econometrically by fixed effects, the treatment and control groups could differ in important ways, such as their consumption response to income shocks and consumption trends. For instance, the model predicts that consumption growth will be very different for constrained versus unconstrained households. Intuitively, we would not want to compare a CEO with a cashier.

To test whether this is an issue, I reweigh the biweekly payroll sample using inverse-propensity-scores to match covariates for ever-rideshare drivers in 2013. I run a logit regression regressing an ever-rideshare indicator on the following covariates: credit utilization, indicators for city, the time-series standard deviations of log spending, log total income and log payroll income, and quartile indicators of spending, total income, payroll income, bank balances, available credit card balances, and net balances. Quartile indicators are used to be non-parametric and to deal with skewness. I choose 2013 because only few drivers have begun driving at this point. Moreover, because the values are all contained in the same calendar year, it is not necessary to control for calendar time, a problem that would arise if I focused on the actual pre-period before Uber entry into each city. Table A1 shows the reweighted descriptive statistics, and Figure A11 shows the propensity scores before and after reweighting. After reweighting, the descriptive statistics, particularly debit variables, move much closer in line.

C Additional Results

C.0.1 Continuously Employed

The reduced-form findings for the full sample make it clear that many rideshare drivers face a severe reduction in main job earnings before beginning rideshare. This sample differs from my biweekly sample because I do not restrict to households with strict biweekly income. Results for this group for log weekly spending (excluding gasoline), payroll income over a biweekly period, and weekly net balances, are shown in Figure A8.
Unlike for the full sample, Figure A8 Panel A, indicates that this group sees small, long-run gains in consumption spending. Panel B shows no statistically significant short or long-run losses in payroll income. In Panel C, net balances decline in the weeks leading up to starting rideshare, although in the long-run, net balances recover.

C.0.2 Long-run Rideshare Drivers

About 25 percent of rideshare drivers appear to permanently cease rideshare within the first quarter after starting. Perhaps they’ve learned something about their type—that they find driving to have more disutility than they originally thought— or maybe they are kicked out by one of the rideshare companies, such as for having a low rating. The overall results are mixing together a group of rideshare stayers and leavers. I also run the specification focusing on households that maintain at least some payroll income, and whose last rideshare observation is outside of the 1 quarter window. Results (not shown) are almost identical.
“Taxi and Chauffeurs (CPS)” is the weighted count of currently employed individuals with the occupation code “Taxi and Chauffeurs” (occupation code [peio1ocd] 9140) in the Current Population Survey Basic Monthly Files. “Taxi and Chauffeurs (ACS)” is the comparable statistic from the American Community Survey (occupation code peio1ocd 9140). The ACS occurs throughout the year, and so I assign ACS estimates to mid-year.
Figure A2: Taxi Drivers vs. Bus/Truckers in the CPS: Hours and Wages

Source: Current Population Survey Basic Monthly Files. Hours worked (pehrsM1) and hourly wages (preonly) for households in the Merged Outgoing Rotation Groups. “Taxi” refers to “Taxi and Chauffeurs” (occupation code [peio1ocd] 9140) while “Bus/Truck” refers to “Bus drivers” (9120) and “Driver/sales workers and truck drivers” (9130).

Figure A3: Hours and Hours Deviations in the CPS

(a) Usual Hours Per Week

(b) Log(Hours Last Week) - Log(Usual Hours)

Panel A reports usual hours worked as reported by households in the CPS. Panel B shows log deviations between hours households report working last week, compared to their usual weekly hours. Source: CPS Basic Monthly Files, 2013-2016.
Figure A4: Recall and Precision by Category

Figure A5: Cumulative Count of Uber Drivers in the App v. Total Uber Drivers

“Actual” shows the cumulative sum of “Number of New Driver-Partners Starting Each Month in the United States,” from Figure 3 of Hall and Krueger (n.d.). “App Data” is the one-week lag of the number users in the app who have their first observed earnings in the indicated week.
The figure provides a hypothetical example of an individual with multiple observed income streams. In this example, my algorithm treats the series highlighted in green as the primary employer from January 26, 2017 through March 9, 2017. There is a break between the start of a new job on March 30, 2017, and this new job then becomes the primary employer. The period from March 16, 2017 through March 23, 2017 will be dropped. In addition, this hypothetical household has weekly income from another source, highlighted in orange. “Total” payroll income over the period January 26, 2017 through February 2, 2017 will be $3,000 ($2,000+$500+$500).
Figure A7: Biweekly Payroll Timeline

Figure shows the timing of consumption and assets for the sample of biweekly earners. I measure consumption spending over the 14 days following paycheck receipt (black brackets). Measures of the household balance sheet are calculated on the day before payroll income is received (thick black line). In the typical U.S. paycycle income received at date $t$ reflects hours worked in the previous two weeks, usually with a lag of one week in between (red brackets).
In these figures, the sample is restricted to households receiving payroll income at least monthly. Panel A plots the event-study coefficients from estimating equation 12 for log total spending, excluding gasoline spending. In panel B, the dependent variable is payroll income, which is aggregated over a biweekly period. In panel C, the dependent variable is net balances (bank balance - credit card balance). The area between the dashed vertical lines indicates the coefficients are estimated on a balanced sample. 95% confidence intervals are shown in dashed lines around the main estimates. Dependent variables are winsorized at the 1% level.
Figure A9: Gaps Between Account Verification and First Rideshare Pay
Figure A10: Uber's Staggered Geographic Entry

(a) New Uber Cities (Thru.12/2012)

(b) New Uber Cities (Thru.6/2013)

(c) New Uber Cities (Thru.12/2013)

(d) New Uber Cities (Thru.6/2014)

(e) New Uber Cities (Thru.12/2014)

(f) New Uber Cities (Thru.12/2015)
Figure A11: Propensity Score: Before and After Reweighting Control Group
Table A1: Descriptive Statistics (2013)- Reweighted

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Table A2: Empirical Markov Transition Matrix

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