The Impact of the Gig-Economy on Financial Hardship among Low-Income Families

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Abstract

Problem Definition: New work arrangements coordinated by gig-economy platforms offer workers discretion over their work schedules at the expense of traditional worker protections. We empirically measure the impact of expanding access to gigs on worker welfare, with a focus on low-income families.

Academic/Practical Relevance: Understanding the welfare implication of access to gigs informs workers considering working gigs and regulators empowered to protect them. Additionally, firms who rely on this working arrangement may find themselves exposed to increased worker turnover and regulatory intervention if they negatively impact worker welfare.

Methodology: We analyze a novel data set documenting the financial health of a sample of low-income families. We are interested in the likelihood that a family experiences hardship, meaning they fail to pay their bills on time. We leverage the sequential launch of Uber's UberX service across locations to identify the impact of the associated increase in access to gigs on hardship via a difference-in-differences design. The granularity of our data allows exploration of possible mechanisms for our results.

Results: We find that UberX increases hardship among the low-income population, primarily by decreasing overall take-home pay (i.e. annual income less expenses). This is despite a corresponding reduction in income volatility, generally a boon to low-income families who have insufficient savings to weather unexpected dips in earnings.

Managerial Implications: These results caution that gigs can be harmful to the most vulnerable members of society, bolstering the position of Uber drivers suing for employee status and governments seeking to regulate the gig economy. Our analysis of mechanisms driving this result offers guidance for effective regulation of platforms like Uber. Further, we find that gigs offer potential benefits to the low-income population through reduction in income volatility.

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1 Introduction

On-demand peer-to-peer services ('gigs') coordinated by platforms like Uber, Lyft, and Postmates rely on independent workers to provide service. Independent workers enjoy complete control over their work schedules. Workers may use this autonomy to schedule gig work around their existing day jobs to supplement their income, or workers may use gigs as a substitute for more conventional forms of work to increase or improve the timing of their leisure time. The drawback of this independence is the lack of traditional employment protections. In particular, worker autonomy over work hours makes infeasible minimum hourly wage guarantees. Instead platforms pay workers per completed service, so the amount a worker earns depends on the number of consumers seeking service. For example, an hour spent driving for Uber may be a lucrative use of time on a busy night but may not even cover expenses on a slow afternoon. The absence of worker protections from this business model has provoked a string of lawsuits aimed at Uber and Postmates (Lien, 2016; Bhardwaj, 2018) and skepticism that gigs improve worker welfare (McCabe and Devaney, 2015).

The aim of this paper is to understand the impact the gig economy has on worker welfare. In addition to informing workers' choices about participating in the gig economy, our analysis should attract the attention of firms who are increasingly organizing their operations around independent workers. The worker welfare associated with this arrangement impacts worker turnover, as well as the likelihood that regulators intervene. For example, New York City has considered enforcing a minimum hourly wage for rideshare drivers (Siddiqui, 2018) and recently imposed a cap on rideshare drivers (Shapiro, 2018) in the name of driver welfare.

We focus on a specific dimension of welfare, which we call financial hardship. A family experiences financial hardship when it fails to pay its bills on time. Though this measure is related to more accessible indicators of financial stability, like annual income, a family whose income is volatile may appear to be financially stable (i.e. annual income > annual expenses) while still experiencing transient financial hardship. This is particularly likely for families with few savings to draw on in months when expenses exceed earnings. For this reason, we are particularly interested in the welfare of low-income families for whom financial hardship is a pressing concern.

We empirically study changes in financial hardship following an expansion of access to gigs. We employ a novel data set documenting survey responses to detailed questions about low-income families' financial security. These data include an explicit measure of financial hardship, as well as granular information about potential antecedents to hardship. In particular, we conceptualize hardship as a function of the long-run average income earned by a family, the volatility of that income over time, the long-run average expenses of a family, and the volatility of expenses. The richness of our data allows for exploration of not only steady-state causes of hardship (e.g. annual income and expenses) but also transient causes of hardship (e.g. month-to-month variability in income and unexpected expenses).

Gigs represent an opportunity for families to improve their welfare both by increasing income, and reducing income volatility. The flexibility of gigs allows workers to work in their spare time, theoretically allowing workers to increase the time they spend earning, increasing income. Additionally, the flexibility of gigs allows workers to adjust to shocks in other sources of income. For example, a worker who receives fewer shifts than usual at his day job may supplement his income by spending those hours working for Uber. In doing so, the worker avoids finding himself with insufficient funds to cover his rent at the end of the month. These positive effects should have the greatest impact on low-income families, who have the greatest need to supplement their income and are more likely to experience unpredictable work schedules (White, 2015).

However, gigs also have the potential to reduce worker welfare. Gigs empower workers to make their own work schedule, but workers in other contexts have used flexibility to trade money for time (Smithson et al., 2004). Organizational behavior literature suggests that workers are more likely to make this trade the less clear the value of their time is (DeVoe and Pfeffer, 2007; Okada and Hoch, 2004). The dependence of gig pay on demand obfuscates the value of time spent working, especially in comparison to hourly-wage jobs, potentially prompting workers to work less when gigs become available. Furthermore, the lack of a fixed hourly pay rate with gigs may increase income volatility, causing more workers to experience financial hardship. These negative effects on welfare are most likely to affect low-income families, who more frequently work jobs that pay by the hour and are more vulnerable to income volatility (Gunderson and Gruber, 2001; Bania and Leete, 2007). Gigs also impose costs on workers, who are responsible for all on-the-job expenses. These costs may increase both the level and the volatility of workers' expenses. For example, when gigs require the use of a worker's personal resource (e.g. a car), gigs may increase the likelihood of an unexpected repair.

To determine the impact of gigs on worker welfare, we study the effect of the launch of Uber's UberX service on rates of financial hardship. Taking advantage of the geographic and temporal staggering of the launch of UberX across locations, we estimate the causal effect of this launch on financial outcomes via a difference-in-differences design, which controls for time-invariant geographic heterogeneity as well as macroeconomic shocks experienced simultaneously across locations. Our work joins a growing body of literature leveraging the sequential roll-out of gigs in this way (Burtch et al., 2018; Greenwood and Wattal, 2017; Li et al., 2016b; Barrios et al., 2018; Zervas et al., 2017).

Our analysis shows that the entry of UberX leads to significantly higher rates of hardship among low-income families. We test four possible mechanisms for this increase: long-run earnings, long-run expenses, income volatility, and expense volatility. We find that, while UberX lowers income volatility, it also decreases overall take-home pay for low-income families. We find no discernible effect on expense volatility. The net effect is lowered welfare for low-income families.

Our analysis makes two main contributions. First, we caution that gigs can be harmful to the most vulnerable members of society. This bolsters the position of Uber drivers suing for employee status and and governments seeking to regulate Uber and similar platforms. These findings should give us pause when we consider how the new, flexible work arrangements championed by the gig economy will shape the future of work. Second, our analysis gives guidance for how low-income worker welfare might be preserved within the gig economy framework. We find that increased hardship is driven by decreased take-home pay, not increased income volatility. Indeed, we find that gigs decrease income volatility. This suggests that regulations designed to boost per-service payments, like New York's cap on rideshare drivers, are more effective than efforts to reduce income volatility, like proposals to impose a minimum hourly wage. These results highlight the possibility for well-designed gigs to improve the welfare of low-income workers by allowing them to mitigate income volatility.

2 Literature Review

There has been a wealth of recent interest in the operations of the gig economy. Most existing work concerns the design of platform profit-maximizing matching (e.g. Feng et al. (2017); Ozkan and Ward (2017); Hu and Zhou (2015)) and pricing (e.g. Cachon et al. (2017); Bimpikis et al. (2016);

Tang et al. (2016); Hu and Zhou (2017); Taylor (2018); Chen and Hu (2017); Guda and Subramanian (2018)). Of particular relevance are papers focusing on welfare implications of gig-economy platforms and their policies. Cachon et al. (2017) shows surge pricing can benefit consumers by increasing supply availability. Castillo et al. (2017) shows that surge pricing can destroy welfare by sending workers on wild goose chases during times of low demand. Afèche et al. (2018) shows that increasing platform control improves worker welfare and platform profit. Benjaafar et al. (2018) and Nikzad (2018) show that platform efforts to recruit ever more workers do not necessarily destroy worker welfare by increasing competition but can also improve worker welfare by attracting more consumers. Kalkanci et al. (2018) suggests that the gig economy has the potential to increase economic inclusion by providing flexible income sources to low-income populations. In this paper we demonstrate the extent to which this potential is realized.

The gig economy has inspired a number of empirical analyses (Kabra et al., 2018; Karacaoglu et al., 2018; Li et al., 2016a). Many of these studies have focused on estimating supply elasticity (e.g. Chen and Sheldon (2016); Cullen and Farronato (2014); Sheldon (2016); Hall et al. (2017)). Others have compared Uber to conventional taxis, concluding that Uber better utilizes its drivers (Cramer and Krueger, 2016) and that drivers benefit from Uber's compensation scheme relative to the weekly or daily leases common in the taxi industry (Angrist et al., 2017). Our analysis estimates the causal impact of the launch of UberX in a location via a difference-in-differences model. A similar approach has been used to study the effect of the entrance of a gig-economy platform on entrepreneurship (Burtch et al., 2018), DUI citations (Greenwood and Wattal, 2017), congestion (Li et al., 2016b), traffic fatalities (Barrios et al., 2018), and incumbent industry market share (Kroft and Pope, 2014; Zervas et al., 2017).

The spread of gigs represents an increase in the availability of flexible work arrangements. In general, contingent work arrangements have been shown to benefit firms by allowing them to only pay for the workers they need (Kesavan et al., 2014; Milner and Pinker, 2001; Pinker and Larson, 2003). This translates to the ridesharing setting via improved utilization of Uber drivers relative to taxi drivers (Cramer and Krueger, 2016). Workers also stand to benefit from these flexible work arrangements via the discretion allowed workers over their work schedules. Workers with this discretion should be better able to integrate their work with other obligations. In particular, discretion should allow workers to supplement their income from day jobs more easily (most Uber drivers hold another job (Hall and Krueger, 2015)). However, discretion also allows workers to prioritize non-lucrative activities and is not always used to further a worker's career (Smithson et al., 2004).

Gigs also influence the volatility of worker income. The discretion associated with gigs should allow workers to increase their time spent on gig-activities in response to an unexpected decrease in outside income, thereby decreasing income volatility (Farrell and Greig, 2016). This is particularly valuable for low-income families, who typically lack sufficient savings to weather downward shocks to their income (Gunderson and Gruber, 2001; Bania and Leete, 2007). However, because gigs pay per service instead of per hour, gigs also inherently increase per-hour income volatility. This volatility is amplified by dynamic pricing policies, like Uber's Surge Price, which pays workers more per service during times of high demand. Our analysis contributes to the literature studying the effect of income volatility on low-income workers by demonstrating the net effect of these competing forces.

3 Data and Descriptive Statistics

To construct our main dependent variables, we rely on two surveys. The first is the Household Financial Survey (HFS), which documents survey responses of a random sample of taxpayers qualifying for TurboTax's Freedom Edition free tax filing package. To qualify for this "freefile" option, a household must have an adjusted gross income no greater than $33,000 ($66,000 for active duty military personnel) or must have received the earned income tax credit. This restriction allows us to focus our analysis on low-income families, who we suspect will experience the greatest impact from the introduction of UberX. Surveys were administered each year from 2013 to 2017 at the time of tax filing, and the number of respondents varied from year to year. The survey asks questions about financial behaviors, demographics, and location. Survey participants additionally consent to share their anonymized tax returns. Table 1 provides descriptive statistics.

Our main dependent variable, *hardship*, measures financial hardship according to the binary response to, "Was there a time in the past X months when you or someone in your household skipped paying a bill or paid a bill late due to not having enough money?" (1 indicates yes). Note that this question refers to the time interval beginning *twelve* months (i.e. $X = 12$) before the survey in 2013 and 2014, while subsequent years refer only to the interval beginning *six* months before the survey (i.e. $X = 6$). Though this leads to more reports of financial hardship in earlier waves of the survey, the increase happens across the board (as opposed to only in locations with UberX), so this difference across survey years is absorbed by the survey-year fixed effect included in our analysis. Note that all other survey questions used to construct dependent variables in this paper are consistently worded across relevant survey waves.

To explore the mechanisms through which UberX increases financial hardship, we study several additional dependent variables from this survey. One mechanism we consider is income volatility. Respondents are asked:

Which of the following best describes your household's income over the last 6 months?

1. Roughly the same amount each month
2. Roughly the same most months, but some unusually high or low months
3. Often changes quite a bit from one month to the next

We classify respondents who select Choice 2 as experiencing moderate income volatility and respondents who select Choice 3 as experiencing severe income volatility. We also consider respondents who report experiencing any income variability by selecting either Choice 2 or Choice 3. The associated dependent variables are *mod_vol*, *hi_vol*, and *any_vol* respectively, where 1 indicates that a respondent belongs to that category.

The hardship experienced by respondents may also be the result of unexpected expenses. We consider three categories of unexpected expenses: car repairs, medical expenses, and legal expenses. Driving for Uber causes additional wear and tear on a vehicle. When not properly prepared for, this may lead to more frequent unexpected car repairs. Driving for Uber also increases the driver's exposure to vehicle collisions (Barrios et al., 2018), which may lead to medical and legal costs. Compounding potential medical costs is the lack of employer-provided health insurance when working for Uber. To measure the potential increase in these expense categories, we use respondents' answers to the following question:

In the last 6 months, have you or has any member of your tax household:

1. Made an unexpected major repair to a vehicle you own?

2. Had unexpected major out-of-pocket medical expense (e.g., from hospitalization or emergency room visit)?

3. Had unexpected legal fees or legal expenses?

The binary variables, *shock_car*, *shock_med* and *shock_legal*, take the value of 1 for respondents who experienced an unexpected expense in each respective category. Note that questions interrogating respondent income volatility and unexpected expenses are only available for survey waves 2015-2017. Our analysis of these variables uses the corresponding subset of the HFS data.

Finally, we consider respondent gross income (captured by the variable *gross_income*) as reported on the respondent's anonymized tax return. We supplement this analysis by analyzing five waves of the biennial Panel Survey of Income Dynamics (PSID) from 2006-2014. The PSID follows families over time, recording granular information about household income and employment, along with demographic and geographic information. We restrict our attention to the 3,835 households with heads of household that are active in the survey during all of the years studied in this analysis (the survey is primarily administered to heads of household). The PSID is a useful supplement to the HFS for several reasons. First, the PSID breaks household income into its component parts (i.e. income from labor, assets, transfers, etc), allowing us to focus on the component affected by UberX entry: labor income. Further, the PSID includes detailed information about respondent work habits, allowing for more detailed explanations of the results of our analysis. Finally, the panel structure of the PSID allows for controls of individual-specific idiosyncrasies. Table 2 provides descriptive statistics.

The PSID surveys families from all income brackets while the HFS surveys only those which qualify to file their taxes for free. To ensure that our analysis of the PSID reflects outcomes of the population studied in the HFS, we split the PSID data into two groups: those deemed "freefile eligible" and those deemed "freefile ineligible." Lacking information on household adjusted gross income, we assign freefile eligibility based on total reported income. Specifically, families deemed freefile eligible reported total income less than $33,000 in 2010, the last year surveyed before Uber first introduced UberX. We designate freefile eligibility based on 2010 income to ensure that group assignment is not influenced by treatment (in our analysis we consider alternative group assignment criteria). Grouping households in this way allows us to identify outcomes specific to low-income households. Tables 3 and 4 provide descriptive statistics for freefile eligible and ineligible families.

In our analysis, we study the expansion of access to gigs via the launch of Uber's UberX service, which allows ordinary car owners (as opposed to licensed livery drivers) to drive for hire. Uber introduced UberX in 2012 and continues to expand; in 2015 75% of the U.S. population had access to UberX (Hawkins, 2015). Using launch announcements on Uber's blog (uber.com/blog) and in local news outlets, we collect the date of UberX launch for the Metropolitan Statistical Areas (MSAs) represented by respondents to the surveys described above. Tables 5 and 6 illustrate the diffusion of UberX's service to locations represented in each survey.

The sequential launch of UberX across locations lends itself to the difference-in-differences design we employ (Angrist and Pischke, 2008; Bertrand and Mullainathan, 2003). Locations without UberX serve as controls for locations that UberX has entered. Locations are considered treated if UberX has launched there by the end of the horizon considered by the survey. The HFS survey is administered when a respondent files his/her taxes. Lacking information about the exact filing date, we assume survey questions refer to events through April of the survey year. For example, a location is considered treated in survey year 2015 if UberX launched there before April 2015. We make an exception to this assumption when analyzing gross income. Gross income reported on a tax return refers to income earned in the previous calendar year. Consequently, to affect gross income UberX would have to launch before the beginning of the survey year. Similarly, PSID survey questions refer to quantities (e.g. income, work hours) in the year preceding the survey year. For analysis of HFS income and PSID quantities, a location is considered treated if UberX launches before January of the survey year.

We take advantage of the longitudinal nature of both surveys by including relative time dummy variables, which indicate the time remaining and elapsed from treatment (i.e. leads and lags). Causal interpretation with our difference-in-differences design requires treated and control locations to exhibit parallel trends before treatment. In other words, our causal interpretation would be invalid had Uber chosen locations to launch UberX *because* of an existing trend in our dependent variables (or because of an unobserved factor correlated with those dependent variables). Though it is unlikely that UberX enters locations randomly, it is plausible that these decisions are independent of financial outcomes experienced by low-income families. Examination of lead variables enables us to evaluate the appropriateness of this assumption. We account for potential serial correlation in errors produced by this longitudinal design by adjusting for clustering at the MSA level.

Finally, we include in our analysis controls for potential MSA-level heterogeneity. We obtain estimates of population, education, and employment from the U.S. Census. Tables 5 and 6 summarize these variables for each survey.

4 Analysis of Hardship

Our main analysis studies the effect of UberX entry on the likelihood a family experiences financial hardship. Our dependent variable is *hardship*, which indicates whether a respondent failed to pay bills on time some months before the survey (as defined in Section 3). Let i index individuals, j index MSAs, and t index survey years. We estimate:

$$hardship_{ijt} = \alpha_t + \gamma_j + \sum_k \beta_k T_{jtk} + X_{ijt} + \epsilon_{ijt} \tag{1}$$

where α_t is the survey year fixed effect that absorbs macroeconomics shocks felt across MSAs, γ_j is the MSA fixed effect that captures the time-invariant attributes of a MSA, X_{ijt} represents individual characteristics, and T_{jtk} is a relative time dummy variable. In this analysis we measure time in years to match the annual nature of the HFS. Correspondingly, T_{jtk} represents whether UberX enters MSA j k years from time t. Because Uber began offering UberX in 2012 and HFS survey responses span 2013-2017, there are four possible leads and four possible lags. We include as individual characteristics gender, race, education, and marital status. These characteristics do not all vary with time, but they account for variation in the demographical distribution of respondents representing a MSA across time. We further include as time-varying MSA characteristics population, percent of population with a college degree, and employment.

As shown in Table 7, the launch of UberX corresponds to a significant and lasting increase in financial hardship. In spite of the opportunities UberX offers families to improve their financial security, UberX entry makes families more likely to fail to meet their short-term financial obligations. These results are robust to sample selection: Column 1 reports results using all waves of data while Column 2 restricts analysis to data from 2015-2017. Notably, our analysis does not detect any pretreatment trends, indicating that, to the extent UberX launches are not random, they do not target locations with increasing rates of hardship among low-income families. This lends credence to the parallel trends assumption required to interpret these results causally.

5 Mechanisms

We now turn our attention to possible explanations for why freefile-eligible families experience hardship more frequently after UberX launches in their location. We conceptualize hardship as a function of steady-state income and expenses, as well as the volatility of income and expenses. We capture steady-state income through annual income and steady-state expenses through reported annual expenses. We focus on the expense categories within the ten largest components of household spending according to the Bureau of Labor Statistics whose level is likely to be affected by UberX's entry: childcare, medical care, and transportation (Bureau of Labor Statistics, 2018) . UberX may reduce the first by offering flexible work that is easier to schedule around a child's schedule, reducing the need to pay for childcare. The second may be increased by UberX's entry if workers lose employer-sponsored health benefits when they take up Uber driving. The third should certainly increase following UberX's entry as people spend more time driving and burning fuel.

In addition to variables measuring a family's average amount of cash-on-hand, we study the volatility of income and expenses. Especially for families with few savings, transient deviations from the norm can lead families to fail to meet their short-term financial obligations. We capture volatility of income through explicit reports of variability in monthly income, and we use reports of unexpected expenses as measures of expense volatility. We again focus on expense categories whose volatility is likely to be affected by UberX's entry: car repairs, medical expenses, and legal expenses. As shown in Barrios et al. (2018), Uber's launch increases vehicle collisions, potentially exposing drivers to unexpected vehicle damages, medical costs, and legal fees. In the subsections that follow, we consider each of these mechanisms in turn.

5.1 Annual Income

It is natural to expect that UberX's entry could affect the take-home pay of the workers that choose to drive for UberX. Ideally, we would measure this effect through gross income, which measures all earnings less business expenses, including the costs of driving for Uber. As shown in Table 8, analysis of gross income reported in both data sets does not reveal any lasting significant impact of Uber entry. We therefore restrict our attention to income earned from labor. This measure is contained in the PSID and represents the total annual income from wages, tips, commissions, overtime, professional practice as well as the labor portion of any farm or business income earned by the head of household and spouse within a family. Focusing specifically on labor income reduces the noise in our estimation and allows us to detect a significant impact of UberX entry.

We adjust our analysis to leverage the panel structure of the PSID by introducing an individual fixed effect, λ_i. The resulting model is:

$$labor\_income_{ijt} = \alpha_t + \gamma_j + \lambda_i + \sum_k \beta_k T_{jtk} + X_{ijt} + \epsilon_{ijt}. \tag{2}$$

To match with biennial nature of the PSID, time in this model is measured in two-year increments. Further, because the data extend only through 2014, we only include one lag variable (Uber launched in only two MSAs before the end of 2012). The panel structure of the PSID removes the need for most individual level controls; those included - number of children, martial status, and age - vary with time. We further include as time-varying MSA characteristics population, percent of population with a college degree, and employment. We separately analyze the effect of UberX entry on freefile-eligible and freefile-ineligible families.

Table 9 illustrates the relationship between UberX entry and labor income. Freefile-eligible families report lower labor income in locations where UberX is available. This means that families that would benefit the most from supplemental income earn less following UberX entry. In contrast, freefile-ineligible families experience an increase in their labor income from UberX entry. Note that these finding are robust to alternative definitions of freefile eligibility: Columns 3 and 4 use the more generous income limit applied to active duty military personnel (\$66,000) while Columns 5 and 6 apply the original income limit to the average of 2008 and 2010 gross income.

To understand this discrepancy, we examine the working behavior of heads of households and spouses in both freefile eligible and ineligible households. Using as our dependent variables the reported work hours of head, the work hours of spouse, and the household's total work hours in estimation equation (2) yields the results in Table 10. Following the launch of UberX, heads of household tend to *decrease* their work hours. In contrast, spouses report working more after

UberX launches in their location. The net number of hours worked in freefile-eligible families declines, resulting in lower earnings.

Determining the motivation for workers to change their work habits following UberX's launch is outside the scope of this paper. The behavior of spouses is consistent with literature studying the effect of other forms of flexible work on female labor force participation (survey waves before 2015 specifically refer to "spouses" as "wives"). Less intuitive is the decline in hours the head of household spends working. It is possible that UberX encourages, either through competition or imitation, employers to rely more heavily on contingent labor, reducing the hours available to individual workers. It is also possible that the reduction in hours stems from a demand side effect. For example, organizational behavior literature would predict that, because the value attached to an hour spent working for Uber is less certain that an hour spent working at a fixed hourly rate, switching to Uber from an hourly wage job would lead workers to work less, all else equal. In both cases, we should expect hourly wage earners, who are disproportionately represented among the freefile-eligible population, to be the most affected. Unfortunately, this contributes to the increased rates of hardship in this population found in Section 4.1.

The results above raise a question of omitted variable bias. Specifically, does UberX enter locations with higher income inequality? While this is possible, we suspect this is not driving our results. To begin with, Tables 9 and 10 do not demonstrate a significant pretreatment trend. Only Table 9 Column 1 has a significant pretreatment relative time dummy variable, but this significance is not preserved under alternative definitions of freefile eligibility and may be the result of regression to the mean. Further, for an income-inequality trend to explain Table 10, rising income inequality would need to be the result of increasing scarcity of work for low-income workers. However, income inequality since the 2008 recession (the time horizon covered by both surveys) has been driven by wage stagnation while unemployment has been on the decline (Shambaugh and Nunn, 2017; Bartash, 2014). This suggests that changes in income and work behavior following UberX entry are the result of UberX's launch.

5.2 Annual Expenses

In addition to affecting the level of earnings families expect, UberX likely affects their expenses. The most obvious expenses affected by UberX are transport costs. As independent contractors, Uber drivers are responsible for expenses they incur on the job, including gasoline, for example. Of the remaining categories that contribute most to average household expenses, Uber is most likely to affect medical expenses and child care expenses. Uber does not offer employer-sponsored health care, so drivers may find themselves paying out of pocket if they forfeit such a benefit to drive for Uber. Uber may have a positive impact on domestic expenses, like childcare. If the flexibility offered by Uber allows drivers to plan around the schedules of their children, they may avoid paying for outside help.

Using the PSID, we construct the variables *childcare*, *medical*, and *gasoline* to capture the annual dollars spent by a family on child care, out-of-pocket medical expenses, and gasoline. We substitute these dependent variables into Equation (2) to estimate the effect of UberX's entry on the level of these expenses. Table 11 reports the results. Columns 1 and 2 show no significant impact of Uber on child care or medical expenses. It is possible that drivers do not use Uber to spend more time caring for their children. It is also possible that those who opt into driving for Uber did not pay for outside child care to begin with. The results in Column 2 indicate that workers appreciate the value of employer-sponsored benefits and tend not to sacrifice them to drive for Uber (or at least purchase new health insurance plans on government-sponsored exchanges). However, Uber drivers do incur significantly higher gasoline expenses, as reported in Column 3.

Though UberX does not drive higher child care or medical costs, it does place the burden of Uber-related business expenses on drivers by design. Taken together with the reduction in earnings reported in Section 5.1, this implies that UberX's launch reduces families' net take home pay.

5.3 Income Volatility

To evaluate the effect of UberX's launch on income volatility, we return to data provided by the HFS. We study the likelihood that a family experiences moderate, severe, or any income volatility. To do this, we re-estimate Equation (1) substituting *mod_vol*, *hi_vol*, and *any_vol* as our dependent variables. Note that because these variables are available for survey waves 2015-2017, there are only two possible lead variables.

Table 12 demonstrates that the entry of UberX *decreases* reports of moderate income volatility. As shown in Column 1, this effect is significant and sustained following UberX's launch. Analyzing reports of severe income volatility does not reveal any effect of UberX entry (Column 2), perhaps because relatively few (12%) respondents fall in this category. Combining reports severe and moderate income volatility reduces the precision of UberX's effect on income volatility, as shown in Column 3, but continues to indicate that income volatility decreases following UberX's entry. Pretrends remain absent in these analyses, indicating UberX's launch is the cause of these changes in income volatility.

These results are an interesting addition to the literature studying income volatility and its effects in low income populations. It is established that income volatility is dangerous for families with few savings to draw upon if their regular income does not materialize. This might lead one to conclude that the fee-per-service payment structure of gig work would be inherently damaging for this population. However, gigs also provide a mechanism to counter income volatility. Specifically, gigs allow workers to adjust their hours in response to earnings from either the platform or from outside sources. Our findings demonstrate that this agency counteracts the extra income volatility gigs might impose from their fee-per-service payment model.

5.4 Expense Volatility

The final potential drivers of hardship is expense volatility. It is possible that driving for Uber introduces more frequent unexpected expenses, exhausting savings and leading families to fail to pay their bills on time. We focus on expense categories whose volatility existing literature has determined is likely to be affected by UberX's entry: car repairs, medical expenses, and legal expenses. Greater use of a driver's vehicle may lead to more frequent component failures and associated unexpected repairs. Further, as shown in Barrios et al. (2018), Uber's launch increases collisions, potentially exposing drivers to unexpected vehicle damages, medical costs, and legal fees.

Using the HFS data, we construct the variables *shock_car*, *shock_med*, and *shock_legal* to indicate whether a family experienced an unexpected expense in each category. We substitute these measures as the dependent variable in Equation (1) to estimate the effect of UberX entry on expense variability. These variables are only available for survey waves 2015-2017, so there are only two possible lead variables. The results, reported in Table 13 indicate that UberX does not significantly increase expense volatility. This suggests that, while Uber may cause more collisions, Uber drivers themselves may not be the responsible party. We conclude that cost volatility is not a driving force behind the increased rates of hardship reported in Section 4.

Taken in sum, our results indicate that the rise in hardship documented in Section 4 is attributable to the decline in net take home pay resulting from UberX's entry. Reduced net income leaves workers with a smaller buffer against unanticipated shocks. These shocks are fewer because of UberX - we find that UberX reduces income shocks and has no significant effect on expense shocks. However, the reduction in income volatility is insufficient to compensate for the reduction in total income.

6 Discussion

There is an open discussion about how to protect worker welfare in markets with independent workers and the extent to which workers need protecting. On one hand, independent workers are empowered to adjust their work hours in response to their needs, conceivably increasing income and averting hardship. However, workers that substitute gig work for traditional labor also have the freedom to work less than they would have otherwise. Independent workers who are paid per service also bear the risk associated with uncertain demand, increasing income volatility.

We show that, as currently operated, UberX is not beneficial to families with sufficiently low incomes to qualify to file their taxes for free. Families in the population report having a harder time meeting their financial obligations after UberX has launched in their location. We attribute this increase in hardship to reduced net take-home pay - workers in locations with UberX report working fewer hours and earning less than their compatriots without UberX. Moreover, Uber drivers are responsible for their on-the-job expenses, further reducing take-home pay. Financial hardship is partially mitigated by reductions in income volatility following UberX's launch, but this is insufficient to fully compensate for workers' lower pay.

Our analysis makes two main contributions. First, we caution that gigs can be harmful to the most vulnerable members of society. This bolsters the position of Uber drivers suing for employee status and governments seeking to regulate Uber and similar platforms. However, we also find evidence that the effect of UberX's entry depends on socio-economics. Unlike freefile-eligible families, freefile-ineligible families experience a boost in income following UberX's launch. This differential effect suggests that, as currently operated, gig-economy platforms like Uber should avoid positioning themselves as an alternative to low-income hourly wage jobs. These platforms may be better served targeting middle income workers who stand to gain from the gig work arrangement.

Second, our analysis gives guidance for how low-income worker welfare might be preserved within the gig economy framework. We find that increased hardship is driven by decreased take-home pay, not increased income volatility. Indeed, we find that gigs decrease income volatility. This suggests that regulations designed to boost per-service payments, like New York's cap on rideshare drivers, are more effective than efforts to reduce income volatility, like proposals to impose a minimum hourly wage. These results preserve the hope that some form of gig work may improve the welfare of low-income families by allowing them to mitigate income volatility while ensuring sufficient overall earnings.

These recommendations would be further informed by a deeper dive into the reasons why freefile-eligible workers work less following UberX's entry. We are unable to observe in our data whether reduced work hours are voluntary (e.g. workers uses Uber's flexibility to work less) or involuntary (e.g. a worker's employer reduces his hours because of imitation of or competition with Uber). There may be important behavioral components to a worker's decision to voluntarily reduce his hours. The entrance of UberX may create spillover effects that influence the labor practices in other industries that are worth analyzing. We hope that this open question will inspire inquiries in this direction.

We acknowledge that our analysis relies on self-reported financial outcomes, which can be subject to error or bias. However, this format allows us to measure an important but elusive marker of welfare, which we call hardship. This measure of welfare is particularly relevant to the population we study; families living paycheck to paycheck are primarily concerned with their ability to meet their short-term obligations, and only secondarily concerned about long-run savings. Future work with granular transaction data recording income, bill arrivals, and bills paid would confirm our results are not driven by bias in self-reporting.

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7 Tables

Table 1: Summary Statistics for HFS

Survey Year	Respondents	Gross Income	% Hardship	% Married	% White	% Female	% College Degree
2013	14077	17243	59	16	73	61	44
2014	6939	16374	50	14	77	59	51
2015	17980	15017	41	13	81	51	37
2016	18455	15430	39	13	81	51	37
2017	25922	16246	36	12	71	51	38

Notes: This table documents summary statistics for each year studied of the HFS survey. From right to left columns refer to the year in which the survey was administered; the number of survey participants; average gross income of respondents; percentage of the respondent population that identifies as white, and female, respectively; the percentage of the respondent population holding a college degree.

Table 2: Summary Statistics for PSID Respondents

Survey Year	Respondents	Income	Labor Income	Head Labor Hours	Spouse Labor Hours	% Married	Age	Children
2007	3835	65518	55958	1763	751	57	46	0.85
2009	3835	67744	59419	1653	722	57	47	0.83
2011	3835	64261	56693	1547	699	58	49	0.76
2013	3835	67539	61068	1532	689	57	51	0.75
2015	3835	68588	60974	1491	671	57	53	0.70

Notes: This table documents summary statistics for each year studied of the PSID survey. From right to left columns refer to the year in which the survey was administered; the number of survey participants; average annual income of respondents; average annual income from labor; average annual hours spent working by head of household; average annual hours spent working by spouse; percent of respondent population that is married; average age of respondent population; average number of children.

Table 3: Summary Statistics for Freefile-Eligible PSID Respondents.

Survey Year	Respondents	Income	Labor Income	Head Labor Hours	Spouse Labor Hours	% Married	Age	Children
2007	1609	23237	19721	1209	262	33	48	0.76
2009	1609	19927	17527	1057	208	33	50	0.71
2011	1609	11536	10131	840	149	32	52	0.64
2013	1609	16932	13456	906	173	32	54	0.60
2015	1609	18255	14287	893	169	31	57	0.56

Notes: This table documents summary statistics of freefile-eligible families for each year studied of the PSID survey. From right to left columns refer to the year in which the survey was administered; the number of survey participants; average annual income of respondents; average annual income from labor; average annual hours spent working by head of household; average annual hours spent working by spouse; percent of respondent population that is married; average age of respondent population; average number of children.

Table 4: Summary Statistics for Freefile-Ineligible PSID Respondents

Survey Year	Respondents	Income	Labor Income	Head Labor Hours	Spouse Labor Hours	% Married	Age	Children
2007	2234	96080	82224	2161	1105	74	42	0.91
2009	2234	102354	89744	2083	1092	75	44	0.91
2011	2234	102182	90400	2055	1096	76	46	0.89
2013	2234	104228	95510	1983	1062	76	48	0.86
2015	2234	105139	94652	1920	1031	75	50	0.78

Notes: This table documents summary statistics of freefile-ineligible families for each year studied of the PSID survey. From right to left columns refer to the year in which the survey was administered; the number of survey participants; average annual income of respondents; average annual income from labor; average annual hours spent working by head of household; average annual hours spent working by spouse; percent of respondent population that is married; average age of respondent population; average number of children.

Table 5: Summary Statistics for MSAs Appearing in the HFS

	Totals		MSA Averages			
Survey Year	MSAs	MSAs with UberX	Population	Employees	% College Degree	Respondents
2013	310	4	782483	295078	27	45
2014	309	34	790683	301337	27	22
2015	310	154	796773	307047	27	58
2016	311	208	802148	312588	28	59
2017	311	259	809516	318566	28	83

Notes:This table documents summary statistics of MSAs featured in the HFS survey. From left to right columns refer to the year in which the survey was administered; the number of unique MSAs; the number of MSAs with UberX by April of the survey year; the average MSA population; the average number of employed persons per MSA; the percent of the MSA population holding a college degree; and the average number of respondents per MSA.

Table 6: Summary Statistics for MSAs Appearing in the PSID

	Totals		MSA Averages			
Year	MSAs	MSAs with UberX	Population	Employees	% College Degree	Respondents
2007	241	0	887843	372959	26	16
2009	242	0	907319	353404	26	16
2011	241	0	947840	350553	27	16
2013	240	2	966123	370518	28	16
2015	236	127	996722	391550	28	16

Notes: This table documents summary statistics of MSAs featured in the PSID survey. From left to right columns refer to the year in which the survey was administered; the number of unique MSAs; the number of MSAs with UberX by the beginning of the survey year; the average MSA population; the average number of employed persons per MSA; the percent of the MSA population holding a college degree; and the average number of respondents per MSA.

Table 7: Difference in Differences Model of the Effect of UberX Entry on Hardship

	Dependent variable:	
	hardship	
	2013-2017	2015-2017
4 years after UberX entry	0.035**	0.058**
	(0.017)	(0.026)
3 years after UberX entry	0.024**	0.036*
	(0.012)	(0.021)
2 years after UberX entry	0.023**	0.028*
	(0.009)	(0.016)
1 year after UberX entry	0.020***	0.019
	(0.007)	(0.012)
1 year before UberX entry	Omitted	
2 years before UberX entry	0.004	0.007
	(0.009)	(0.021)
3 years before UberX entry	−0.018	
	(0.013)	
4 years before UberX entry	−0.032	
	(0.020)	
MSA Fixed Effect	Y	Y
Survey Year Fixed Effect	Y	Y
Individual Attributes	Y	Y
MSA Attributes	Y	Y
Observations	82,630	61,918
R^2	0.114	0.092
Adjusted R^2	0.110	0.087
Residual Std. Error	0.467 (df = 82288)	0.465 (df = 61582)

Notes: *hardship* indicates if a family failed to pay bills on time recorded in the HFS. Column 1 uses all available HFS data while Column 2 uses only the 2015-2017 waves. Individual attributes include race, gender, education, and marital status. MSA attributes include population, employment, and education. Standard errors are clustered at the MSA level. *p<0.1; **p<0.05; ***p<0.01

Table 8: Difference in Differences Model of the Effect of UberX Entry on Gross Income

	Dependent variable:		
	Gross Income		
	HFS	PSID Freefile Eligible	PSID Freefile Ineligible
4 years after UberX entry	−51.497		
	(487.103)		
3 years after UberX entry	−16.093		
	(363.373)		
2 years after UberX entry	32.004		
	(247.571)		
1 year after UberX entry	257.295*		
	(154.318)		
1 year before UberX entry	Omitted		
2 years before UberX entry	119.692		
	(200.756)		
3 years before UberX entry	−209.656		
	(313.629)		
4 years before UberX entry	211.948		
	(743.628)		
After UberX entry		−1,758.111	13,366.160*
		(2,548.438)	(7,450.418)
2 years before UberX entry		Omitted	
4 years before UberX entry		−672.921	599.202
		(1,756.815)	(5,578.505)
6 years before UberX entry		−441.471	1,696.144
		(2,189.555)	(4,821.661)
8 years before UberX entry		−697.861	9,222.533
		(2,953.890)	(11,106.130)
MSA Fixed Effect	Y	Y	Y
Survey Year Fixed Effect	Y	Y	Y
Individual Fixed Effect	N	Y	Y
Individual Attributes	Y	Y	Y
MSA Attributes	Y	Y	Y
Observations	69,635	8,025	11,132
R^2	0.140	0.488	0.538
Adjusted R^2	0.136	0.338	0.406
Residual Std. Error	9,766.710 (df = 69292)	24,787.440 (df = 6203)	134,705.800 (df = 8650)

Notes: Column 1 analyzes HFS data while Columns 2 analyze PSID data. HFS gross income is reported on a respondent's tax return. Gross income in the PSID refers to total reported income less business expenses. Column 1 individual attributes include race, gender, education, and marital status. Columns 2 and 3 individual attributes include marital status, age, and children. MSA attributes include population, employment, and education for all columns. Standard errors are clustered at the MSA level. *p<0.1; **p<0.05; ***p<0.01

Table 9: Difference in Differences Models of the Effect of UberX Entry on Labor Income

	Dependent Variable: Labor Income					
	Model 1		Model 2		Model 3	
	Freefile-Eligible	Freefile-Ineligible	Freefile-Eligible	Freefile-Ineligible	Freefile-Eligible	Freefile-Ineligible
After UberX entry	−1,842.964**	6,364.151*	−1,595.612**	9,972.260*	−1,720.096**	6,295.876*
	(788.216)	(3,696.353)	(676.664)	(5,152.687)	(843.293)	(3,812.487)
2 years before UberX entry			Omitted			
4 years before UberX entry	−1,838.728**	2,397.320	−766.355	1,582.762	−996.307	1,936.378
	(896.370)	(3,170.105)	(842.465)	(3,982.453)	(713.648)	(3,162.469)
6 years before UberX entry	244.782	328.945	−205.148	−1,377.042	−927.820	1,392.773
	(1,381.816)	(4,036.311)	(1,186.943)	(5,554.436)	(986.918)	(4,155.401)
8 years before UberX entry	954.005	5,871.301	851.121	4,336.804	1,376.914	7,018.735
	(1,737.417)	(5,421.627)	(1,584.875)	(6,900.010)	(1,412.660)	(5,538.373)
MSA Fixed Effect	Y	Y	Y	Y	Y	Y
Survey Year Fixed Effect	Y	Y	Y	Y	Y	
Individual Fixed Effect	Y	Y	Y	Y	Y	Y
Time-Varying Individual Attributes	Y	Y	Y	Y	Y	Y
Time-Varying MSA Attributes	Y	Y	Y	Y	Y	Y
Observations	8,045	11,170	12,420	6,795	7,655	11,600
R^2	0.634	0.767	0.686	0.761	0.654	0.766
Adjusted R^2	0.527	0.700	0.597	0.688	0.552	0.700
Residual Std. Error	15,401.270 (df = 6223)	52,813.970 (df = 8688)	18,652.580 (df = 9693)	63,539.340 (df = 5218)	14,123.410 (df = 5914)	52,262.180 (df = 9027)

Notes: Dependent variable, labor income, includes all income from wages, tips, commissions, overtime, professional practice and the labor portions of farm and business income recorded in the PSID. This tables reports three different definitions of freefile eligibility: total annual income in 2010 < \$33,000 (Columns 1 and 2); total annual income in 2010 < \$66,000 (Columns 3 and 4); average annual income in 2008 and 2010 < \$33,000 (Columns 5 and 6). Individual attributes include marital status, age, and children. MSA attributes include population, employment, and education for all columns. Standard errors are clustered at the MSA level. *p<0.1; **p<0.05; ***p<0.01

Table 10: Difference in Differences Model of the Effect of UberX Entry on Work Hours

	Dependent variable:			
	Head Work Hours	Spouse Work Hours	Total Household Work Hours	
			Freefile Eligible	Freefile Ineligible
After UberX entry	-69.607^{***}	47.427^{**}	-88.856^{**}	15.025
	(21.512)	(20.143)	(42.313)	(39.511)
2 years before UberX entry		Omitted		
4 years before UberX entry	−40.437	27.140	−60.200	11.881
	(24.685)	(21.156)	(49.298)	(43.323)
6 years before UberX entry	−51.088	3.654	−48.919	−61.025
	(33.054)	(30.227)	(67.348)	(65.011)
8 years before UberX entry	−43.610	2.354	−19.582	−83.980
	(42.108)	(38.628)	(83.597)	(74.182)
MSA Fixed Effect	Y	Y	Y	Y
Survey Year Fixed Effect	Y	Y	Y	
Individual Fixed Effect	Y	Y	Y	Y
Time-Varying Individual Attributes	Y	Y	Y	Y
Time-Varying MSA Attributes	Y	Y	Y	Y
Observations	19,175	19,175	8,045	11,170
R^2	0.731	0.835	0.713	0.707
Adjusted R^2	0.658	0.790	0.629	0.624
Residual Std. Error	612.377 (df = 15067)	431.785 (df = 15067)	733.477 (df = 6223)	779.708 (df = 8688)

Notes: The dependent variables in this table are the annual hours spent working by the head of household (Column 1); the annual hours spent working by the spouse (Column 2); and the total annual hours spent working by the head of household and spouse (Columns 3 and 4) as reported in the PSID. A family is freefile-eligible if total 2011 income < \$33,000. Individual attributes include marital status, age, and children. MSA attributes include population, employment, and education for all columns. Standard errors are clustered at the MSA level. *p<0.1; **p<0.05; ***p<0.01

Table 11: Difference in Differences Model of the Effect of UberX Entry on Expenses

	Dependent variable:		
	childcare	medical	gasoline
After UberX entry	10.038	−98.430	14.810*
	(55.661)	(121.571)	(8.722)
2 years before UberX entry		Omitted	
4 years before UberX entry	−68.492	−161.104*	0.432
	(59.962)	(87.601)	(8.318)
6 years before UberX entry	−110.460	−209.864**	−0.467
	(94.351)	(95.876)	(9.556)
8 years before UberX entry	−38.755	−197.036	7.015
	(113.109)	(147.777)	(10.002)
CBSA Fixed Effects	Y	Y	Y
Survey Year Fixed Effects	Y	Y	Y
Individual Fixed Effects	Y	Y	Y
Individual Attributes	Y	Y	Y
CBSA Attributes	Y	Y	Y
Observations	19,087	18,547	18,837
R^2	0.580	0.375	0.574
Adjusted R^2	0.465	0.197	0.455
Residual Std. Error	1,533.386 (df = 14979)	2,309.813 (df = 14439)	143.163 (df = 14729)

Notes: The dependent variables in this table are the annual dollars spent on child care (Column 1), out-of-pocket medical expenses (Column 2), and gasoline (Column 3) as reported in the PSID. Individual attributes include marital status, age, and children. MSA attributes include population, employment, and education for all columns. Standard errors are clustered at the MSA level. *p<0.1; **p<0.05; ***p<0.01

Table 12: Difference in Differences Model of the Effect of UberX Entry on Income Volatility

	Dependent variable:		
	mod_vol	hi_vol	any_vol
	(1)	(2)	(3)
4 years after UberX entry	-0.062^{**}	0.022	-0.040
	(0.028)	(0.023)	(0.030)
3 years after UberX entry	-0.046^{**}	0.014	-0.032
	(0.022)	(0.018)	(0.024)
2 years after UberX entry	-0.037^{**}	0.014	-0.023
	(0.017)	(0.013)	(0.017)
1 year after UberX entry	-0.035^{***}	0.007	-0.029^{**}
	(0.012)	(0.008)	(0.012)
1 year before UberX entry		Omitted	
2 years before UberX entry	-0.014	0.011	-0.004
	(0.017)	(0.014)	(0.019)
MSA Fixed Effect	Y	Y	Y
Survey Year Fixed Effect	Y	Y	Y
Individual Attributes	Y	Y	Y
MSA Attributes	Y	Y	Y
Observations	61,943	61,943	61,943
R^2	0.018	0.010	0.014
Adjusted R^2	0.013	0.004	0.008
Residual Std. Error (df = 61607)	0.477	0.331	0.423

Notes: The dependent variables in this table indicate whether a family experienced moderate income volatility (Column 1), severe income volatility (Column 2) or either moderate or severe income volatility (Column 3) as reported in the HFS. Individual attributes include race, gender, education, and marital status. MSA attributes include population, employment, and education. Standard errors are clustered at the MSA level. *p<0.1; **p<0.05; ***p<0.01

Table 13: Difference in Differences Model of the Effect of UberX Entry on Unexpected Expenses

	Dependent variable:		
	shock_car	shock_med	shock_legal
	(1)	(2)	(3)
4 years after UberX entry	−0.023	0.016	−0.023
	(0.040)	(0.025)	(0.016)
3 years after UberX entry	−0.010	0.017	−0.015
	(0.031)	(0.019)	(0.012)
2 years after UberX entry	−0.015	0.006	−0.013
	(0.022)	(0.015)	(0.009)
1 year after UberX entry	−0.010	−0.010	−0.010
	(0.013)	(0.010)	(0.008)
1 year before UberX entry		Omitted	
2 years before UberX entry	0.001	−0.025	0.003
	(0.019)	(0.017)	(0.012)
MSA Fixed Effect	Y	Y	Y
Survey Year Fixed Effect	Y	Y	Y
Individual Attributes	Y	Y	Y
MSA Attributes	Y	Y	Y
Observations	61,847	61,849	61,850
R^2	0.028	0.026	0.020
Adjusted R^2	0.023	0.021	0.014
Residual Std. Error	0.459 (df = 61511)	0.371 (df = 61513)	0.263 (df = 61514)

Notes: The dependent variables in this table indicate whether a family incurred unexpected vehicle expenses (Column 1), unexpected medical expenses (Column 2), or unexpected legal expenses (Column 3) as reported in the HFS. Individual attributes include race, gender, education, and marital status. MSA attributes include population, employment, and education. Standard errors are clustered at the MSA level. *p<0.1; **p<0.05; ***p<0.01