The Self-Employment Effects of the EITC in the Gig Economy*

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Abstract

The Earned Income Tax Credit (EITC) is structured to encourage work. There is a large literature documenting the EITC's impact on labor supply and self-employment. Most of the existing work suggests that self-employment responses to the EITC are largely changes in reporting rather than real changes in employment. However this might not be surprising as starting a business and earning self-employment income can be risky, uncertain, and logistically complicated, potentially keeping low-income workers from pursuing self-employment in response to the EITC. The advent of gig employment platforms, such as Uber, might reduce the barriers to entering self-employment. Exploiting state-level EITC policy and the roll-out of Uber across markets, I document how the self-employment response to the EITC differs when there are gig opportunities available in the market. I find that the EITC leads to small, but significant increases in self-employment when Uber is operating in the market. These effects are concentrated among single-headed households and lead to income changes that shift households towards larger credits.

Keywords: EITC, self-employment, gig economy, Uber

JEL Codes: H24, J22, L26

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1 Introduction

There is a large literature documenting the labor supply effects of the Earned Income Tax Credit (EITC). One consistent result is that self-employment income is particularly responsive to EITC parameters. This could be due to the fact that self-employed workers have more control over their work schedule and the amount of income they generate. However, many have documented that this pattern is more consistent with people adjusting income reporting for tax purposes, not a real change in labor supply or income generation (Kuka, 2014; LaLumia, 2009; Saez, 2010). When filing taxes, self-employment income does not face third party verification, meaning it is much easier to manipulate self-employment income to the EITC maximizing level. Simultaneously, for many low-income households in the EITC-eligibilty income range, starting a business and earning self-employment income can be risky, uncertain, and complicated from a logistical and administrative perspective. This might help explain why there is little evidence of real self-employment effects.

However, the advent of "gig" work, where individuals perform tasks as independent contractors through online platforms, has potentially reduced the entry barriers to self-employment income. By contracting through the platform, workers can experience the flexibility of self-employment and also benefit from the platform's administration without having to be entrepreneurs. This could reduce the riskiness, uncertainty, and administrative burden of self-employment. It is possible the EITC leads to real changes in self-employment when gig opportunities are available to low-income households in ways that have not been explored previously. In this paper, I ask, "how is the self-employment response to the EITC different when there are viable gig employment opportunities in the local labor market?"

To do this, I exploit the roll-out of two sources of variation. First, I exploit variation across states and years in the generosity of state and federal EITC levels. These state tax credits build on the federal credit and typically follow the same eligibility rules. Previous work has found that these state-level EITCs increase employment and reported self-employment income (Bastian and Lochner, 2022; Wilson, 2022) and federal EITC claiming (Neumark and Williams, 2020). Second, I exploit variation across local labor markets in the rollout of Uber. Uber is one of the first, and perhaps the largest gig platform, with over 460,000 independently contracted drivers by 2015 (Hall and Krueger, 2018). Using this variation, I estimate how the earned income tax credit affects self-employment when gig self-employment opportunities are available in the market. Importantly, I estimate these effects using microdata from the 2005-2019 American Community Survey (ACS) obtained through IPUMS (Ruggles et al., 2022) rather than administrative tax data. The ACS is an annual, one percent random sample of US households where individual anonymity is protected and is not used for tax purposes. As such, respondents have no incentive to misreport self-employment activity. This allows me to capture any real changes in self-employment activity and earnings that are not contaminated by tax reporting incentives which must be considered when using tax data (Garin et al., 2022).

Focusing on unmarried households where the head has a high school degree or less (who are likely to be affected by the EITC schedule), I estimate that the effect of EITC generosity on real self-employment rates are twice as large in areas where Uber is present, suggesting that real behavioral responses to the EITC are larger when the barriers to self-employment are smaller. A $1,000 increase in the maximum EITC the household is eligible to receive is associated with an additional 0.2 percentage point (3 percent) in the self-employment rate and 2.5 percent increase in self-employment income if Uber is available in the local labor market. These results are robust to various specifications and controls for potential differential trends. I also do not observe effects in placebo specifications among highly-educated single households, who are unlikely to be eligible for the EITC.

Increases in EITC generosity also lead to differential shifts in the income distribution of less-educated unmarried households when Uber is present in the local labor market. Total income shifts away from the tails of the EITC schedule towards the middle, where the EITC credit is the largest. There is a corresponding change in self-employment income, with households moving from zero or very low self-employment to self-employment income between \$10,000 and \$25,000, leading to total incomes where the EITC is the largest. These patterns are consistent with gig opportunities increasing households' strategic self-employment to increase EITC refunds. Because the data are not tied to tax reporting, this is unlikely to be due to strategic reporting.

This work is related to two strands of literature. The first, explores the impact of the EITC on self-employment, with a focus on strategic self-employment reporting (Kuka, 2014; LaLumia, 2009; Saez, 2010). This current paper expands this literature by looking at real self-employment responses to the EITC when lower-risk, self-employment opportunities (in the form of gig employment) are available in the local labor market. This can help us better understand the overall welfare consequences of the EITC. The second strand of literature explores the rise in self-employment in administrative data, finding evidence of growing gig employment in some sectors (like ride services) (Abraham et al., 2019), but also evidence that much of the rise in self-employment is due to strategic reporting of EITC-elgible households, not gig employment (Abraham et al., 2021; Garin et al., 2022). The current paper adds to this literature by focusing on the interaction of gig employment and the EITC, which has not been fully explored. The previous work has only looked at the interaction between the EITC and gig employment under conditions where only reporting, not real self-employment can respond. Although the EITC is unlikely to explain the entire increase in gig employment, it is possible that the work incentives of EITC and the access to self-employment job amenities through gig employment interact to affect real self-employment among some groups.

This study has two contributions. First, there is little evidence of how the gig economy affects eligibility and participation in safety net and low-income transfer programs. Given the rise in these types of work, and the flexibility that it can afford to constrained households, like single-headed households, understanding this interaction has important policy implications. Second, by exploring how the EITC affects self-employment, in non-tax Census survey data (where there is no direct benefit to misreporting), especially when there is a change in low-income self-employment opportunities, we can better understand to what extent the EITC is increasing self-employed work and not just having an effect on reporting.

The effect of the EITC on self-employment of less-educated households in places with Uber is significant, but small. Access to gig opportunities, in the form of Uber, double the self-employment response to the EITC, but the base is low. On the whole, this would suggest that some groups are likely to increase real self-employment in response to the EITC if some of the barriers to self-employment, such as increased risk, uncertainty, and administrative burden are removed, but the effects are not widespread. Given existing work that suggests household surveys like the ACS undercount gig employment, these point estimates are likely biased downward, suggesting the interaction between accessible self-employment and EITC work incentives could be larger.

2 Background

2.1 The Earned Income Tax Credit

The EITC is a refundable federal tax credit for low-income households and is one of the largest anti-poverty tools in the US (Hoynes and Patel, 2018; Jones and Ziliak, 2022). In 2019 the EITC transferred 64.5 billion dollars to 26.7 million tax units (Internal Revenue Service, 2022). Over time, states have implemented supplemental state EITC policies that generally pay out an additional percentage of the federal EITC. Between 2005 and 2018, 11 states have introduced a state EITC (see Figure 1). These policies vary in generosity, from 3.5 percent to 50 percent or more.

The generosity of the credit depends on household earned income and introduces explicit work incentives. As seen in Figure A1, a household with zero dollars of earned income gets zero dollars of credit. As earned income increases, the credit increases until it eventually plateaus and then is clawed back. This wage subsidy at the very bottom theoretically encourages entry into the labor force. A large literature exploiting variation across different time periods documents significant effects of the EITC on labor force participation (elasticies ranging from 0.3 to 0.7) (Bastian, 2020; Eissa and Liebman, 1996; Neumark and Williams, 2020; Whitmore Schanzenbach and Strain, 2021).[1] Existing work has also exploited the state-level policies to identify the effect of the EITC on labor supply and other outcomes (Bastian and Jones, 2021; Bastian and Lochner, 2022; Michelmore and Pilkauskas, 2021; Wilson, 2022).

Many low-income, EITC-eligible households, like those headed by single individuals, face competing demands on their time (like employment, home production, and child care), so the flexibility of self-employment might make it an appealing option. EITC expansions lead to more self-employment reporting among eligible households in administrative tax data (Kuka, 2014; LaLumia, 2009), but the self-employment response is an order of magnitude smaller (still statistically significant) when using survey data, like the Current Population Survey (CPS) (Kuka, 2014). Using tax data, Saez (2010) finds significant bunching in the income distribution of tax units with self-employment income around the first kink of the EITC schedule, but no corresponding bunching for tax units without self-employment. These patterns suggest that the rise in self-employment in tax data is likely due to changes in reporting (either reporting previously undisclosed or ficticious self-employment income), rather than real changes in labor supply.[2]

The real self-employment labor supply responses to the EITC might be small because of the risk, uncertainty, and administrative burden associated with self-employment. Starting a business is risky, with 20 percent of new businesses closing in their second year (Bureau of Labor Statistics, 2021). Identifying a product or service to profitably market can be challenging and uncertain. Running a business efficiently often requires diligent adminis-

[1]Kleven (2022) calls the extensive margin response into question, claiming employment gains among single mothers in the 1990s are due to welfare reform and absent in other periods. Whitmore Schanzenbach and Strain (2021) suggest that this result is due to differences in the time frame over which employment is measured, differences in business cycle controls, and the inclusion of all unmarried women.

[2]There is some evidence that wage-earners adjust at the intensive margin to the EITC, leading to shifts in the income distribution, and this response becomes stronger when there is more knowledge or information about the EITC in the local area (Chetty et al., 2013).

trative attention to finances and logistics. Low-income household, and particularly single parent households, might lack the finances and bandwidth to effectively maintain or grow self-employment opportunities. The rise of "gig" work, might provide a way for these constrained households to benefit from the flexibility of self-employment, while avoiding some of the risk and administrative burden of self-employment.

2.2 The Growth of the Gig Economy

Over the last 10 years we have observed a proliferation of online platforms and apps that connect consumers to contracted services. These include things like ride-share, food delivery, short term rentals, and pay-per-task services. Collectively, these non-traditional work arrangements are known as gig work or the gig economy (Abraham et al., 2018). Although the advent of gig work has captured the attention of the popular press, the scope of gig work is much harder to identify in the data. Administrative data from Census Bureau data on nonemployer businesses (Abraham et al., 2021, 2019) and from tax records (Garin et al., 2022) show a large, steady increase in self-employment from 2000 through about 2015. The data indicate a 651,000 person increase (nearly 300 percent) in the number of nonemployer businesses in ground passenger transportation (Abraham et al., 2019), with most of this growth in taxi and limousine services (Abraham et al., 2021). This is consistent with a large increase in ride-share drivers, like Uber or Lyft. Using 1099 information returns, Garin et al. (2022) decompose the overall rise in self-employment to identify a large rise in online platform gig work between 2013 and 2018, on the order of one percent of the overall workforce. Previous work has found that people use gig work, specifically rideshare, to smooth consumption when they lose more traditional payroll work (Koustas, 2020).

The swift ascent of gig employment is considerably muted in household surveys, like the CPS (Abraham et al., 2021, 2019). This discrepancy is in part due to the way people in household surveys misinterpret independent contractor relationships (e.g., driving for Uber is self-employment not wage employment) or the focus of household surveys on the primary source of employment (Abraham et al., 2021). This does not mean that we should only focus on administrative data and household surveys should be completely discounted. As Garin et al. (2022) document, much of the rise in self-employment since 2000 is concentrated among tax units in the EITC-eligibility income region and is not present when focusing on self-employment with third-party reporting, like 1099 information returns. Also, much of the rise in self-employment pre-dates the major online platforms like Uber. These authors suggest that most of the rise in self-employment in administrative data is a reporting response to the EITC, not a real change in gig-related self-employment. Although the household surveys undercount reported self-employment, they might better capture changes in real self-employment than administrative tax data.

2.3 The Roll-out of Uber

As noted above, the rise in gig employment is most noticeable in the ride-share sector, with a nearly 300 percent rise in nonemployer businesses in that sector (Abraham et al., 2019). Uber and Lyft are arguable the two largest gig platforms. For this reason, I will exploit the roll-out of Uber across metropolitan areas to proxy for access to self-employment gig opportunities. Lyft was founded four years after Uber, and in most cases followed Uber to a local market.

Uber was launched in 2009 and the first ride-share request was made on July 5, 2010 in San Francisco. Using Uber roll-out data from Hall et al. (2018) and press releases on the Uber newsroom website, I identify when ride-share services began being offered in different cities. I then link cities to the associated Census Bureau core-based statistical area (metropolitan or sometimes micropolitan statistical area) to identify local markets where Uber is available, which I will refer to as metropolitan areas.[3] As seen in Figure 1, the roll-out was slow initially, only reaching seven metropolitan areas by the end of 2011.[4] By the end of 2013,

[3]For some cities, the Uber website indicates that serves are offered, but does not provide an entry date. For these cities, a research assistant looked at local news headlines to identify the month and year Uber ride-share services began in the city.

[4]San Francisco, San Jose, New York, Seattle, Chicago, Boston, Washington DC.

Uber had entered 31 other areas, but there was a wide-spread roll-out to 161 metropolitan areas in 2014 and 2015. From there expansion slowed, only reaching an additional 32 areas by the end of 2019. As Hall et al. (2018) show, entry of Uber into a local market significantly increases Uber's penetration as captured by the number of drivers and Google Trends interest in Uber.

3 Data

To estimate the effects of the EITC and access to gig employment on self-employment I will use the American Community Survey (ACS) between 2005 and 2019, obtained through IPUMS (Ruggles et al., 2022). The ACS is an annual, one percent random sample of households. Importantly, the ACS is conducted by the Census Bureau and does not have any tax implications for respondents, meaning there is no incentive to misreport self-employment, as in administrative tax data.

In the ACS, respondents report on employment, worker class (self-employed or work for wages), and intensive margin labor supply measures like weeks work and usual hours worked. If an individual has multiple sources of employment, they are to report the class of worker for the job that they spent the most time in during the reference week. As such, this measure of self-employment will not capture individuals who hold a main job and drive for Uber on the side. For this reason, I also examine households' various sources of income including self-employment income and total income. Individuals can report self-employment income, even if their main job was payroll employment. I can also examine whether or not the household has non-zero self-employment income as an indicator, to proxy for self-employment work that might occur outside of the individual's primary job.

Given the nature of the EITC schedule, I want to focus on EITC-eligible households. Rather than restrict the sample by household income, which would be endogenous to the EITC if there is a response, I focus on households where the household head is unmarried and has a high school degree or less. This restriction will help limit the sample to households targeted by the program and is similar to restrictions made in other work exploring the effects of the EITC (Bastian and Michelmore, 2018; Michelmore and Pilkauskas, 2021). More of the distribution of income among these households overlaps with the EITC schedule allowing me to target households who are more likely to be eligible for the EITC. Given the rich, existing literature exploring differential effects of the EITC by marital status, I also provide estimates for married households for completeness.

In the ACS, I use a household's state of residence and the number of children in the household to determine EITC generosity. The federal EITC schedule varies with the number of eligible children, while state-level EITC policies build on this variation. Throughout my analysis, I will focus on the maximum EITC the household would be eligible to receive based on these characteristics, irrespective of household income, as income is potentially endogenous to the EITC. I also use the household's current metropolitan statistical area (MSA) of residence to identify whether or not the family lives in a market where Uber is present.

The roll-out of Uber to locations was not random. It first began in the largest cities, but the main roll-out in 2014 and 2015 was widespread. As seen in Table 1, areas that were early to adopt Uber were more diverse, with higher levels of income. However, average characteristics are quite similar between early and late adopting metropolitan areas but quite different in areas that never adopted Uber (before the end of the sample in 2019). As seen in column (4), none of the averages are statistically different when focusing on early and late adopters in the same state. In most states, and particularly in states with state-level EITCs, there are multiple metropolitan areas where Uber is rolled out. As such, there is within state variation in both EITC generosity and the presence of Uber. For this reason I will verify that the effects are robust to only looking at areas that adopt Uber, and to controlling for metropolitan area-level trends.

4 Empirical Approach and Identification

I will first estimate the average effect of EITC generosity on self-employment as follows

$$Y_{imst} = \beta_1 Max\ EITC_{ist} + \gamma_{st} + \delta_m + \alpha_e + \varepsilon_{imst} \tag{1}$$

The outcome of interest is whether or not the household (either head or spouse if there is one) reported any self-employment. Metropolitan area fixed effects (δ_m) and the number of qualifying children fixed effects (α_e) are included to account for unobserved differences in employment across cities and household sizes. State-by-year fixed effects are included, making this a comparison between households who face varying EITC generosity in the same state and year. The coefficient β_1 represents the effect of an additional \$1,000 in the maximum EITC the household is eligible to receive. Standard errors are corrected for clustering at the state-level. In my baseline specification I estimate effects for unmarried, less-educated households, but I provide estimates for the full sample of less-educated households in the Appendix (Table A1).

This generalized difference-in-differences follows other work exploring the effect of EITC generosity on labor supply (Bastian and Jones, 2021; Bastian and Lochner, 2022; Wilson, 2020). The *Max EITC* is the maximum EITC (federal plus state) the household is eligible to receive based on the year, number of children in the family that meet EITC-eligibility criteria[5], and the state of residence. The year and number of qualifying children dictate the federal EITC schedule. The state of residence and year determine the add-on percentage from the state-level policy. This measure does not exploit variation in EITC generosity based on location in the income distribution, as this is potentially endogenous to the EITC.

I will next explore how these effects vary depending on the presence of ride share gig

[5] In general, an EITC-qualifying child must be under age 19 by the end of the year. However, eligibility is extended to children who are under age 24 and a full-time student for at least five months of the year. The household roster structure of the ACS makes it impossible to identify children that qualify in this second group if they are no longer living with their parents, so I do not count children between 19 and 24 towards the household's number of qualifying children.

opportunities, as proxied by Uber operating in the local market, as follows

$$Y_{imst} = \beta_1 Max\ EITC_{ist} + \beta_2 Max\ EITC_{ist} * Uber\ in\ Area_{mt} + \beta_3 Uber\ in\ Area_{mt} + \gamma_{st} + \delta_m + \alpha_e + \varepsilon_{imst} \quad (2)$$

The outcome is the same as above, but *Max EITC* is now interacted with whether or not Uber is currently present in the metropolitan area (m). The key coefficient of interest is β_2, which provides a test of whether or not the self-employment response is larger in metropolitan areas where opportunities to drive with Uber are available. This specification is similar to a generalized triple difference, there is variation across time, across states, and across metropolitan areas, but also by the number of eligible children. By including state-by-year, metropolitan area, and number of qualifying children fixed effects, I am comparing self-employment responses of people in areas with Uber to other people in the same state, but without Uber, partialling out level differences in employment by the same number of qualifying children. The identifying assumption is that self-employment of households in Uber-exposed areas would have evolved like self-employment of households with the same number of qualifying children in unexposed areas in the same state if the change in EITC generosity had not occurred.

Since employment measures relate to the individual's primary job, I also examine other outcomes to capture changes in self-employment. I estimate equation (2) looking at whether or not the household reports any self-employment income, any employment, wage employment, and the amount of total income and self-employment income.[6]

[6] In Appendix Table A2 I also provide income estimates using the inverse hyperbolic sine transformation, which approximates a natural log transformation but is defined at zero, and is meant to allow a percent effect interpretation. However, as recent work suggests, inverse hyperbolic sine transformations can be sensitive to how the original variable is scaled and lose the percentage interpretation (Chen and Roth, 2023).

5 Results

In Table 2 I report the results from equations (1) and (2). Among unmarried households with a high school degree or less, a \$1,000 increase in the maximum EITC is associated with a significant 0.5 percentage point increase in household-level self-employment. This point estimate is similar to previous estimates (0.4 percentage points) using non-tax data (Kuka, 2014). When interacting maximum EITC with the presence of Uber, a \$1,000 increase in the maximum EITC is associated with a significant 0.2 percentage point increase in self-employment for regions where Uber is operating. Comparing the estimates of β_1 and β_2 from equation (2), the self-employment response is twice as large in places where gig opportunities in the form of Uber are present. Consistent with gig work reducing barriers to entering self-employment, the EITC leads to significantly more self-employment in areas where Uber is operating particularly among single-headed households. These effects suggest a large difference in behavior for this group but are economically quite small. A thousand dollar increase in the maximum EITC only increases self-employment rates by about three percent (off of the base of 6 percent). Since this measure of self-employment does not capture self-employment on the side, this estimate could be biased downward.[7]

I also report effects using other measures of self-employment, wage employment, and income, in Table 2. Among single households, a \$1,000 increase in the maximum EITC is associated with a 0.2 percentage point increase in reporting any self-employment income in Uber adopting areas, consistent with the effects on self-employment. Even when using more inclusive measures of employment the differential effects of the EITC in places where rideshare gig employment opportunities are available are similar. This would suggest that although the presence of gig opportunities does increase the self-employment response to the EITC, it does not induce large swings in self-employment work. Consistent with the existing literature on the employment effects of the EITC, a \$1,000 increase in the maximum

[7] As seen in Appendix Table A1, the interacted effects for married households are smaller and insignificant in areas with Uber present.

EITC is associated with a 1.1 percentage point increase in any employment among single-headed households, but there is no significant differential increase in any employment in areas where Uber is operating. Although the EITC is associated with higher wage employment among single-headed households (consistent with existing work), this effect is reversed in places where Uber operates, consistent with people shifting out of wage employment into self-employment rather than Uber adopting places simply experiencing more employment growth. This would suggest the self-employment results do not just capture differential employment trends in places that do and do not adopt Uber. Finally, a $1,000 increase in the maximum EITC is associated with a $33 (2.5 percent) increase in self-employment ("business") income in Uber adopting areas. However, the presence of Uber in the MSA actually reduces the effect of EITC generosity on total income by $163 off of a baseline effect of $357. To understand if this shift to self-employment made households worse off, we must determine to what extent this behavior was strategic.[8]

These estimates are based on measures of self-employment where there is no tax-related reporting motive and thus reflect changes in real self-employment behavior. They suggest that a small segment of the population adjusts their real level of self-employment when the EITC becomes more generous if there are gig opportunities available. Most previous work has found minimal real self-employment responses to the EITC, but those estimates do not explore differences by gig employment opportunities. Based on these estimates, real self-employment responds to the EITC when there is access to gig employment that reduces the barriers to entering self-employment.

As much of the previous literature exploring self-employment responses to the EITC has focused on strategic reporting, we might also be interested in understanding if the changes in real self-employment are strategic in ways that affect the size of the EITC. Using household

[8]As there might be differences in cost of living across place, we also examine the inverse hyperbolic sine of income in Appendix Table A2. Interpreting this as percent effects we see an additional 1.6 percent increase in self-employment income and no additional effect on total income of the EITC when Uber is present. When looking solely at people with positive income, we estimate positive coefficients but they are small, suggesting minimal intensive margin responses.

levels of income, I re-estimate equation (2), where the outcome is a binary variable for having income within a specific range (e.g., \$5,000-\$10,000). I estimate this for \$5,000 income bins ranging all the way to \$50,000, just past the EITC phase-out. I also include a bin for income under \$0. I then plot the β_2 coefficients on the interaction between the EITC and presence of Uber for each of these bins in Figure 2. For reference, I provide the parameters of the EITC schedule from 2010. When looking at the single-headed households, there is a significant decline in the share of households having total income between \$0 and \$10,000. There is a corresponding rise in reporting income between \$10,000 and \$35,000. This pattern is consistent with strategic, but inexact earning that moves households away from the tails of the EITC schedule, where the credit is small, towards the middle where the credit is larger. When looking at self-employment income there is a similar pattern. There is a significant decline in low levels of self-employment (\$0-\$5,000) with an increase in reporting \$10,000-\$15,000 of self-employment (where the first kink in the EITC schedule is) and over the next few bins across the plateau and initial part of the phase out. Overall, these results suggest that in places with gig employment opportunities there is a small, but significant effect of the EITC on real self-employment behavior and these behavioral changes are strategic, moving people towards larger EITC credits.

6 Robustness

The effects of the EITC on self-employment in area where Uber operates are robust, as documented in Table 3. Including state-by-year-by-number of qualifying children fixed effects makes this a comparison between families of the same size in the same year, when some have access to Uber, while others do not. Even with this specification I estimate a similarly sized effect. The baseline specification includes state-by-year effects, but the estimates are similar if state and year effects are included separately. The effects are also insensitive to excluding number of qualifying children fixed effects. One concern is that metropolitan areas that adopt Uber might be on different self-employment trends than areas that do not adopt

Uber, or adopt it later. As seen in Table 1, early and late adopting metropolitan areas are quite similar along many observable dimensions. If I restrict the sample to places that ever adopt Uber during the analysis period, the identifying assumption is weaker, rather than needing adopting of Uber within a state to be as good as random, now only the timing of adoption within a state needs to be as good as random. The effect is nearly identical if I make this restriction. Also, adding metropolitan area by year fixed effects to account for any differential trends of places that do and do not adopt Uber (or adopt it earlier or adopt it later) does not affect the coefficient. The estimates are similar if I restrict the sample to adopting areas and include metropolitan area by year fixed effects.[9]

The effects also do not show up among populations we would ex ante expect to be ineligible. Throughout, I have restricted the sample to households where the head has a high school degree or less. More educated workers tend to earn higher wages and are less likely to be EITC eligible. If I restrict the sample to single households headed by someone who has more than a four year degree, there is no effect of the EITC or the interaction between EITC and Uber availability on self-employment (Table A3). If these effects were simply driven by steeper trends in self-employment in areas that adopt Uber we would have expected to see similar effects for this group.

The effects are present among households where the head is a single woman or a single man. They also seem to be driven by households that are Non-Hispanic White or Hispanic and younger (Table A4). The ACS also allows me to examine outcomes directly tied to gig-work (Table A5). The interaction between EITC generosity and Uber availability is associated with longer commute times for less-educated, single households. These households

[9]A recent literature exploring the property of two-way fixed effects models suggest this estimation strategy might yield biased results (Callaway and Sant'Anna, 2020; Goodman-Bacon, 2020). However, this strategy is exploiting variation in treatment timing across two dimensions (EITC and Uber), continuous variation in EITC generosity, and using individual-level repeated cross-sections. The existing corrections are not designed to incorporate this. However, following guidance of Goodman-Bacon (2020), the state-by-year effects will make this a within state comparison, approximating the stacked estimation. Since the timing of the EITC is the same within state, and the timing of EITC roll-out is mostly compressed to a few years, this minimizes concerns about comparing earlier and later treated units. In fact, if I separately estimate equation (2) for each state, the weighted average of these effects is similar to the OLS estimate.

are also less likely to report having any health insurance or public health insurance, consistent with increased self-employment. There is no evidence that people shift into the taxi driver/chauffeur occupation group, but these results should be interpreted with the caveat that this occupation group is very small and only captures individuals' primary occupation as they described it. Finally, the ACS asks how many vehicles are kept at the home for the family's use. The effects do not vary based on this measure, although the vast majority of households report having at least one or multiple vehicles available for use.

7 Conclusion

There is a large literature documenting the effects of the EITC on employment and self-employment. Most of this work has found that most of the self-employment response to the EITC, is a change in reporting. However, starting a business often involves uncertainty, risk, and administrative obstacles, so many individuals who might want to respond to the EITC through self-employment might not. In this paper, I explore how the effects of the EITC on self-employment might be different in the gig economy. The roll-out of app based gig platforms like Uber and Lyft allow people to engage in self-employment with much smaller administrative burdens and risk. By reducing barriers to entering self-employment, gig opportunities might result in more real self-employment responses to the EITC.

Exploiting state level EITC generosity and the roll-out of Uber across markets, I find that less-educated households in markets where ridesharing through Uber is available significantly increase their self-employment when the EITC becomes more generous. These results are based on data from the American Community Survey. Because this survey is not tied to tax filing, there are not incentives to misreport self-employment, suggesting that this represents a real change in self-employment behavior. This shifting in self-employment is consistent with strategic behavior, with households moving away from the tails of the EITC schedule where credits are smaller, towards the middle, where credits are larger.

Although the self-employment response to the EITC is twice as large in areas with gig opportunities, the effects are small in magnitude. Across specifications, a $1,000 increase in the maximum EITC leads to a 0.2 percentage point (3 percent) increase in being self-employed in Uber-exposed areas among unmarried, less-educated households. Removing barriers to entering self-employment does increase the elasticity of self-employment to the EITC, but this increase is small suggesting that barriers to entering self-employment do not dramatically affect the real self-employment response to the EITC.

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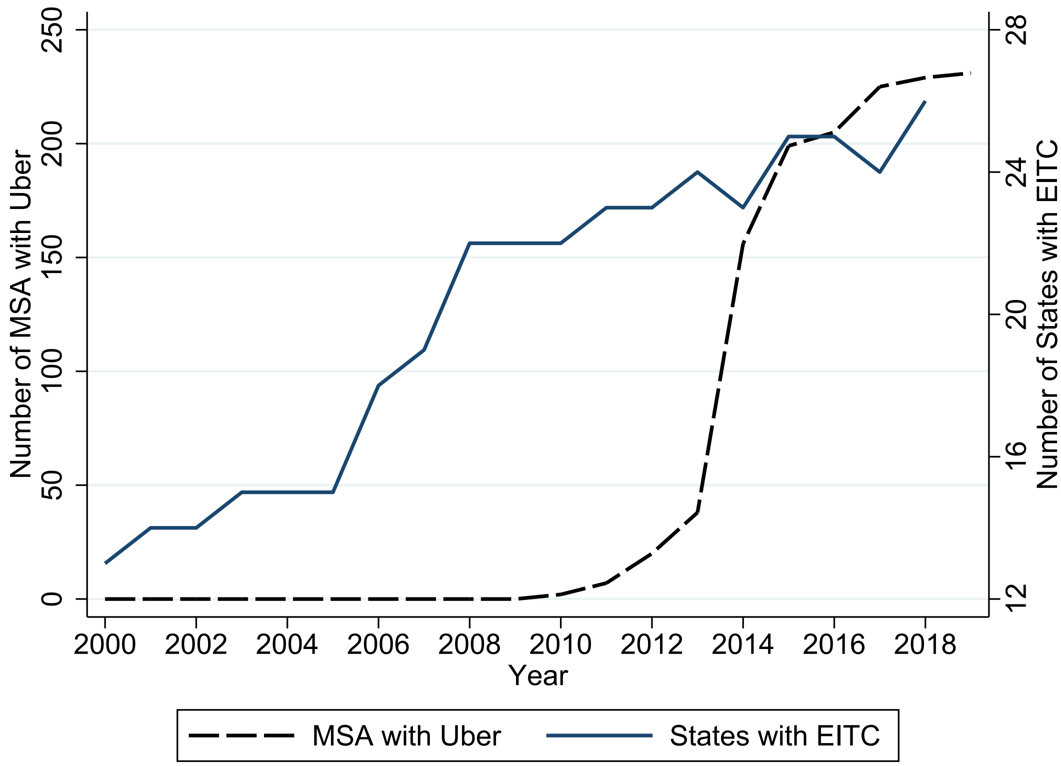
8 Figures and Tables

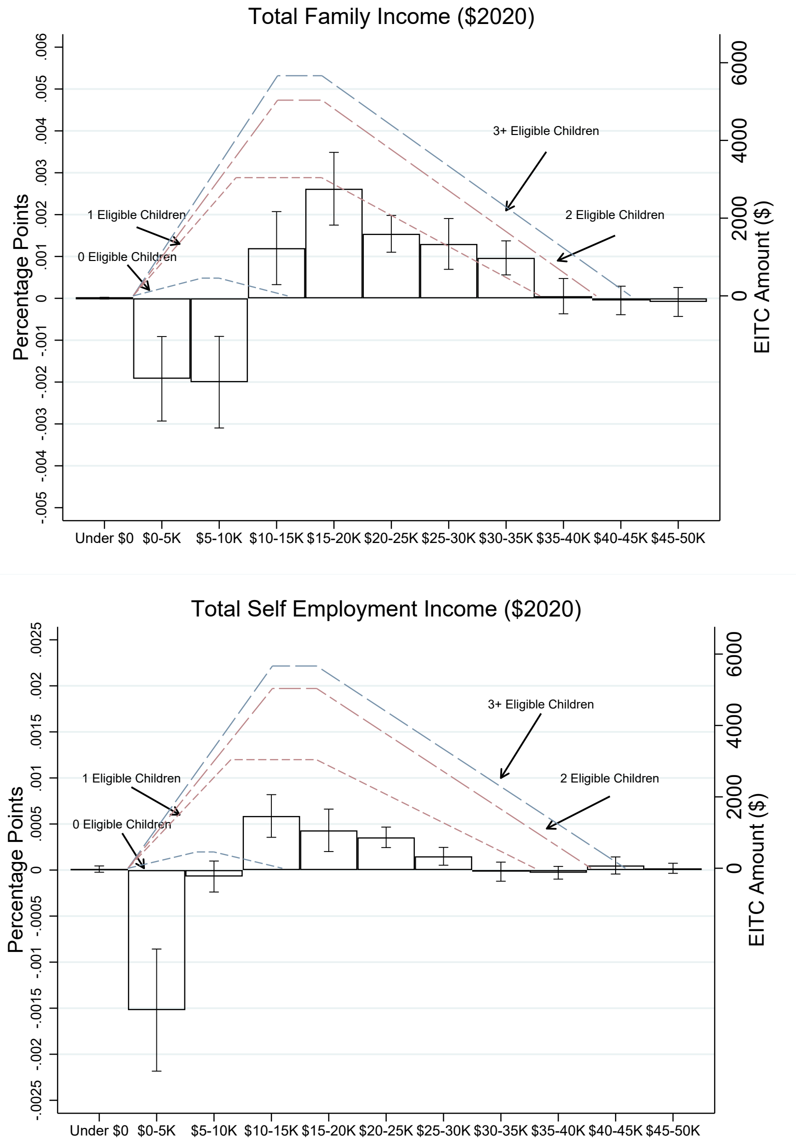
Figure 1: States with an EITC and Metropolitan Areas with Uber Operating in the Area



NOTE: The number of Metropolitan Areas with Uber in operation is plotted on the left axis. The number of states with an enacted EITC, of any generosity level, is plotted on the right axis.

SOURCE: Author's own estimates based on data from the Tax Policy Center and NBER Tax Sim (EITC), Uber publications and data from (Hall et al., 2018) (Uber).

Figure 2: Effect of EITC in Uber Areas on Business Income and Total Income Distribution of Single, Less-educated Households



NOTE: Sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less. Only one observation per household is included. The EITC-Uber interaction coefficients from equation (2) are plotted, where the outcome is having income in a given bin. Having $0 of income is included in the bin $0-5k. The maximum EITC is the maximum state plus federal EITC the household is eligible to receive based on the year, state of residence, and number of qualifying children. This is measured in thousands of dollars. State-by-year, metropolitan area, and number of qualifying children fixed effects are included. Standard errors are corrected for clustering at the state-level.

SOURCE: Author's own estimates based on data from Uber publications and data from (Hall et al., 2018) and EITC data from the Tax Policy Institute and NBER Tax Sim.

Table 1: Summary Statistics by Uber Adoption Status

	Uber Before 2014 (1)	Uber After 2014 (2)	No Uber by 2019 (3)	Within State Difference (2)-(1) (4)
Non-Hispanic White	0.48	0.58	0.75	0.07
Non-Hispanic Black	0.23	0.21	0.14	-0.07
Non-Hispanic Other	0.06	0.03	0.04	-0.02
Other	0.23	0.19	0.07	0.02
Hispanic	0.18	0.19	0.18	0.00
Head 18-34	0.33	0.32	0.29	-0.02
Head 35-54	0.16	0.16	0.17	-0.00
Head 55-64	0.34	0.34	0.38	0.01
Married HH	0.00	0.00	0.00	0.00
Single HH	1.00	1.00	1.00	0.00
Head Less HS	0.34	0.32	0.32	0.00
Head HS	0.66	0.68	0.68	-0.00
Any Employment	0.51	0.51	0.46	-0.02
Any Self-Employment	0.07	0.07	0.06	-0.00
Have Self-Employment Income	0.05	0.05	0.05	-0.00
HH Income ($2020)	33977.29	31040.99	29023.89	-2440.84
HH Wage Income ($2020)	21510.27	19166.69	16535.90	-2484.49
HH Self-Employment Income ($2020)	1504.95	1345.25	1387.07	-169.34
Observations	1,024,598	1,097,449	1,414,403	

NOTE: Sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less and was not married. Only one observation per household is included. In column (4) only households in metropolitan areas where Uber has entered by the end of the sample are included. In this specification state-by-year fixed effects are also included to make this a comparison between households in the same state and year, some of whom live in areas that adopted Uber earlier, some of whom live in areas that adopted Uber later. There are no significant differences between areas that adopted Uber before 2014 and after 2014. Standard errors are corrected for clustering at the state-level. $p< 0.01$ ***, $p< 0.05$ **, $p<0.1$ *.

Table 2: Effect of EITC Generosity on Self-Employment of Single, Less-educated Households, by Uber Availability

	Self-Employment			Any	Any Wage	Business	Total
	Any	Any	Business Income>0	Employment	Employment	Income (2020)	Income (2020)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Maximum EITC (1000s)	0.005**	0.002	0.001	0.011**	0.008*	0.557	355.695**
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(43.305)	(168.779)
Maximum EITC (1000s)*Uber in MSA		0.002***	0.002***	0.002	-0.005***	32.796***	-163.199***
		(0.000)	(0.000)	(0.001)	(0.001)	(11.778)	(45.787)
Uber in MSA		0.000	0.001	-0.001	0.002	34.226	-315.550*
		(0.001)	(0.001)	(0.002)	(0.002)	(31.790)	(166.859)
Dependent Mean	0.06	0.06	0.05	0.44	0.52	1321.08	31085.66
Observations	3,536,450	3,536,450	3,536,450	3,536,450	3,536,450	3,536,450	3,536,450

NOTE: Sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less and was not married. Only one observation per household is included. Coefficient from equation (1) are provided in column (1) while coefficients from equation (2) are provided in the other columns. The maximum EITC is the maximum state plus federal EITC the household is eligible to receive based on the year, state of residence, and number of qualifying children. This is measured in thousands of dollars. State-by-year, metropolitan area, and number of qualifying children fixed effects are included. Standard errors are corrected for clustering at the state-level. p< 0.01 ***, p< 0.05 **, p<0.1 *.

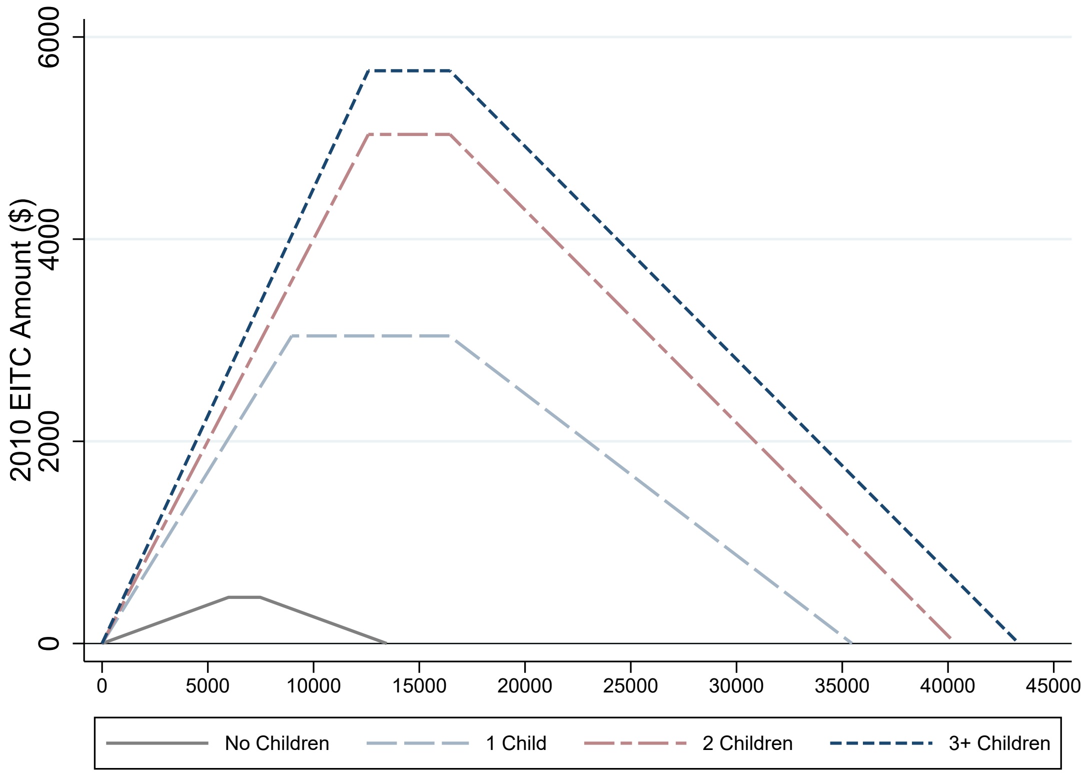
Table 3: Robustness Effect of EITC Generosity on Self-Employment of Single, Less-educated Households, by Uber Availability

	Self-Employment					
	State-by-Year-by-Children F.E.	State and Year F.E.	No Number of Child F.E.	Only Uber Adopting Areas	MSA by Year F.E.	Uber Adopting Areas and MSA by Year F.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Maximum EITC (1000s)	0.000	0.002	0.002***	0.002	0.002	0.002
	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)
Maximum EITC (1000s)*Uber in MSA	0.002**	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Uber in MSA	0.000	0.001*	0.000	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Dependent Mean	0.06	0.06	0.06	0.06	0.06	0.06
Observations	3,535,821	3,536,450	3,536,450	2,122,047	3,536,450	2,122,047

NOTE: Sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less and was not married. Only one observation per household is included. Coefficients from equation (2) are provided. The maximum EITC is the maximum state plus federal EITC the household is eligible to receive based on the year, state of residence, and number of qualifying children. This is measured in thousands of dollars. State-by-year, metropolitan area, and number of qualifying children fixed effects are included unless otherwise indicated in the column title. Standard errors are corrected for clustering at the state-level. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

9 Online Appendix A. Additional Figures and Tables

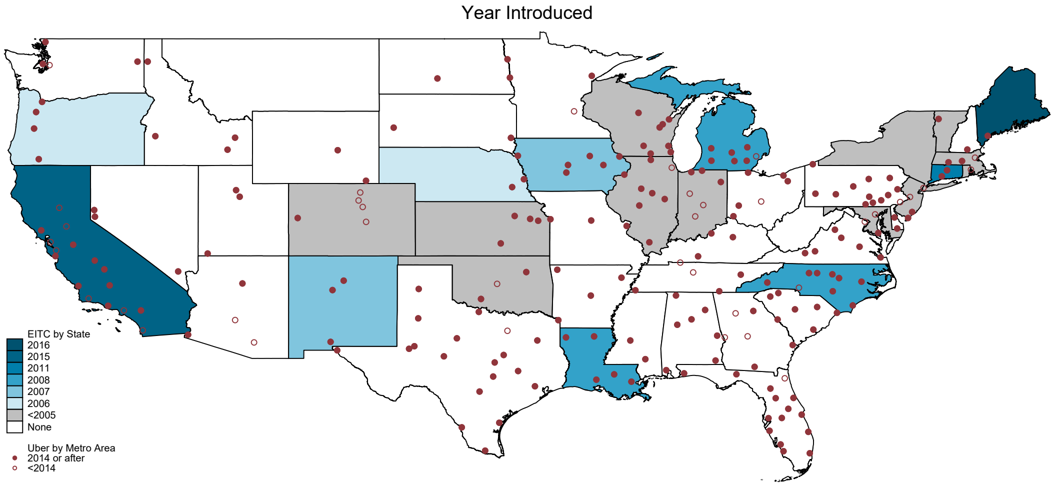
Figure A1: EITC Schedule Parameters for Household with Qualifying Children in 2010



NOTE: The EITC schedule parameters from tax year 2010 are plotted for households with zero, one, two, or three or more qualifying dependents.

SOURCE: Author's own estimates based on data from the Tax Policy Center.

Figure A2: Geographic and Temporal Variation in EITC and Uber



NOTE: The distribution of Metropolitan Areas with Uber in operation and states with a state-level EITC.

SOURCE: Author's own estimates based on data from Uber publications and data from (Hall et al., 2018) and EITC data from the Tax Policy Center and NBER Tax Sim (EITC), Uber publications and data from (Hall et al., 2018) (Uber)

Table A1: Effect of EITC Generosity on Self-Employment of Married, Less-educated Households, by Uber Availability

	Self-Employment		Any	Any Wage	IHS Income	
	Any	Business Income>0	Employment	Employment	Business	Total
	(1)	(2)	(3)	(4)	(5)	(6)
	All High School or Less Headed Households					
Maximum EITC (1000s)	0.001	0.001	0.007	0.006	0.021***	0.005
	(0.002)	(0.001)	(0.005)	(0.004)	(0.005)	(0.015)
Maximum EITC (1000s)*Uber in MSA	0.001*	0.000	-0.000	-0.003***	0.002	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.004)
Uber in MSA	0.004***	0.007***	0.006***	0.004**	-0.011	0.068***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.010)	(0.011)
Dependent Mean	0.11	0.08	0.57	0.63	10.84	0.81
Observations	6,801,370	6,801,370	6,801,370	6,801,370	6,801,370	6,801,370
	Married, High School or Less Headed Households					
Maximum EITC (1000s)	-0.000	0.000	0.002	0.002	0.011**	-0.001
	(0.003)	(0.002)	(0.005)	(0.004)	(0.005)	(0.021)
Maximum EITC (1000s)*Uber in MSA	0.001	-0.000	-0.001	-0.003***	-0.002	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)
Uber in MSA	0.006***	0.010***	0.010***	0.007***	-0.013*	0.100***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.017)
Dependent Mean	0.15	0.12	0.70	0.74	11.40	1.15
Observations	3,264,920	3,264,920	3,264,920	3,264,920	3,264,920	3,264,920

NOTE: In the top panel, sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less. In the bottom panel, sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less and was married. Only one observation per household is included. Coefficients from equation (2) are provided in the other columns. IHS is the inverse hyperbolic sine transformation, which approximates the natural log transformation but is defined at 0. This is the inverse hyperbolic sine of dollars. The maximum EITC is the maximum state plus federal EITC the household is eligible to receive based on the year, state of residence, and number of qualifying children. This is measured in thousands of dollars. State-by-year, metropolitan area, and number of qualifying children fixed effects are included. Standard errors are corrected for clustering at the state-level. $p< 0.01$ ***, $p< 0.05$ **, $p<0.1$ *.

Table A2: Robustness: Effect of EITC Generosity on Income of Single, Less-educated Households, by Uber Availability

	IHS Income		Intensive Margin Only	
	Business	Total	Business	Total
	(1)	(2)	(3)	(4)
Maximum EITC (1000s)	0.013	0.049***	-0.017	0.013
	(0.015)	(0.013)	(0.012)	(0.009)
Maximum EITC (1000s)*Uber in MSA	0.016***	0.002	0.006	0.003*
	(0.004)	(0.003)	(0.005)	(0.002)
Uber in MSA	0.009	-0.014	0.006	-0.021***
	(0.009)	(0.011)	(0.020)	(0.006)
Dependent Mean	0.49	10.33	26648.47	32189.22
Observations	3,536,450	3,536,450	176,580	3,415,499

NOTE: Sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less and was not married. Only one observation per household is included. Coefficient from equation (2) are provided. IHS is the inverse hyperbolic sine transformation, which approximates the natural log transformation but is defined at 0. This is the inverse hyperbolic sine of whole dollars. In columns (3) and (4) only households with positive income are included, to approximate the intensive margin. The maximum EITC is the maximum state plus federal EITC the household is eligible to receive based on the year, state of residence, and number of qualifying children. This is measured in thousands of dollars. State-by-year, metropolitan area, and number of qualifying children fixed effects are included. Standard errors are corrected for clustering at the state-level. $p< 0.01$ ***, $p< 0.05$ **, $p<0.1$ *.

Table A3: Placebo Effect of EITC Generosity on Self-Employment of Most-educated Households, by Uber Availability

	Any Self Employment (1)	Have Self Employment Income (2)
Maximum EITC (1000s)	0.003	0.003
	(0.003)	(0.002)
Maximum EITC (1000s)*Uber in MSA	0.001	0.000
	(0.001)	(0.001)
Uber in MSA	-0.003	-0.003
	(0.002)	(0.002)
Dependent Mean	0.11	0.11
Observations	849,899	849,899

NOTE: Sample restricted to households in the 2005-2019 ACS where the head has an advanced college degree. Only one observation per household is included. Coefficients from equation (2) are provided. The maximum EITC is the maximum state plus federal EITC the household is eligible to receive based on the year, state of residence, and number of qualifying children. This is measured in thousands of dollars. State-by-year, metropolitan area, and number of qualifying children fixed effects are included. Standard errors are corrected for clustering at the state-level. p< 0.01 ***, p< 0.05 **, p<0.1 *.

Table A4: Heterogeneous Effect of EITC Generosity on Self-Employment of Single, Less-educated Households, by Uber Availability

	Female (1)	Male (2)	NH White (3)	NH Black (4)	NH Other (5)	Hispanic (6)	Head 18-54 (7)	Head 55-64 (8)	Head Over 64 (9)
Any Self-Employment									
Maximum EITC (1000s)	0.001	0.001	0.002	0.006***	0.004	-0.002	0.000	-0.006	0.038***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.005)	(0.008)
Maximum EITC (1000s)*Uber in MSA	0.001***	0.002***	0.001***	0.000	0.000	0.002***	0.002***	0.005***	-0.010***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.000)	(0.002)	(0.004)
Uber in MSA	-0.000	0.002	-0.000	0.000	0.016	0.000	0.001	-0.000	0.006***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.016)	(0.003)	(0.001)	(0.002)	(0.002)
Dependent Mean	0.05	0.10	0.07	0.03	0.09	0.08	0.09	0.08	0.03
Observations	2,209,004	1,327,443	2,352,349	571,651	25,521	462,246	1,452,189	618,089	1,522,533
IHS Self-Employment Income ($2020)									
Maximum EITC (1000s)	0.002	0.039*	0.028**	0.022	-0.005	-0.020	0.001	-0.046	0.317***
	(0.013)	(0.019)	(0.014)	(0.015)	(0.067)	(0.014)	(0.014)	(0.042)	(0.095)
Maximum EITC (1000s)*Uber in MSA	0.013***	0.009	0.011**	0.004	0.013	0.018***	0.017***	0.039**	-0.028
	(0.003)	(0.009)	(0.005)	(0.004)	(0.034)	(0.005)	(0.003)	(0.018)	(0.030)
Uber in MSA	0.004	0.037**	-0.001	0.000	0.071	0.020	0.018	0.010	0.020
	(0.007)	(0.015)	(0.009)	(0.016)	(0.208)	(0.022)	(0.015)	(0.023)	(0.021)
Dependent Mean	0.33	0.74	0.50	0.26	0.68	0.71	0.76	0.62	0.18
Observations	2,209,004	1,327,443	2,352,349	571,651	25,521	462,246	1,452,189	618,089	1,522,533

NOTE: Sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less. Only one observation per household is included. Coefficients from equation (2) are provided. IHS is the inverse hyperbolic sine transformation, which approximates the natural log transformation but is defined at 0. This is the inverse hyperbolic sine of dollars. The maximum EITC is the maximum state plus federal EITC the household is eligible to receive based on the year, state of residence, and number of qualifying children. This is measured in thousands of dollars. State-by-year, metropolitan area, and number of qualifying children fixed effects are included. Standard errors are corrected for clustering at the state-level. p< 0.01 ***, p< 0.05 **, p<0.1 *.

Table A5: Effects of EITC Generosity on Gig-Specific Outcomes of Single, Less-educated Households

	Any Self-Employment					
	Vehicle Available	No Vehicle	Taxi Driver/ Chauffer	Commute Time (Minutes)	Has Health Insurance	Has Public Health Insurance
	(1)	(2)	(3)	(4)	(5)	(6)
Maximum EITC (1000s)	0.001	0.005	0.000	0.413**	0.013*	0.022**
	(0.002)	(0.003)	(0.000)	(0.190)	(0.008)	(0.009)
Maximum EITC (1000s)*Uber in MSA	0.002***	0.002***	0.000	0.255***	-0.007***	-0.005***
	(0.000)	(0.001)	(0.000)	(0.043)	(0.002)	(0.002)
Uber in MSA	0.001	-0.003	0.000	-0.355***	0.005*	-0.006
	(0.001)	(0.002)	(0.000)	(0.098)	(0.003)	(0.004)
Dependent Mean	0.07	0.03	0.00	10.96	0.68	0.48
Observations	2,819,917	716,532	3,536,450	3,536,450	3,536,450	3,536,450

NOTE: Sample restricted to households in the 2005-2019 ACS where the head has a high school degree or less. Only one observation per household is included. Coefficients from equation (2) are provided. For columns (1)-(2) the outcome is any self-employment, but the effects are estimated separately by whether or not the household has a car available for use. There is no information on who own the vehicle. The outcome in column (3) is if someone in the household is in occupation code 9140, Taxi Driver/Chauffer. The outcome in column (4) and (5) are binary measures that equal one if the individual has health insurance and public health insurance. The maximum EITC is the maximum state plus federal EITC the household is eligible to receive based on the year, state of residence, and number of qualifying children. This is measured in thousands of dollars. State-by-year, metropolitan area, and number of qualifying children fixed effects are included. Standard errors are corrected for clustering at the state-level. $p< 0.01$ ***, $p< 0.05$ **, $p<0.1$ *.