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DRIVING THE GIG ECONOMY

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ABSTRACT

Using rich administrative tax data, we explore the effects of the introduction of online ridesharing platforms on entry, employment and earnings in the Taxi and Limousine Services industry. Ridesharing dramatically increased the pace of entry of workers into the industry. New entrants were increasingly likely to be young, female, White and U.S. born, and to combine earnings from ridesharing with wage and salary earnings. Displaced workers found ridesharing to be a substantially more attractive fallback option than driving a taxi. Ridesharing also affected the incumbent taxi driver workforce. The exit rates of low-earning taxi drivers increased following the introduction of ridesharing in their city; exit rates of high-earning taxi drivers were little affected. In cities without regulations limiting the size of the taxi fleet, both groups of drivers experienced earnings losses following the introduction of ridesharing. These losses were ameliorated or absent in more heavily regulated markets.

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I. Introduction

The rise of the "gig economy" has attracted wide attention from both scholars and the popular media. Much of this attention has focused on the increase in jobs mediated through various online platforms. The introduction of smartphone apps and other web-based applications that facilitate the acquisition of goods and services directly from individual providers is widely perceived to have accelerated the pace of change in the organization of work, with important effects on both workers and firms. In this paper, we study the dramatic growth over the period from 2010 through 2016 of self-employment in the Taxi and Limousine Services industry (NAICS 4853) following the introduction of Uber and other ridesharing services.

Our first set of research questions relate to the effects of ridesharing's introduction on the entry of new drivers into the industry. By lowering the barriers to entry, the entrance of online platform rideshare companies made it easier to earn money as a driver. We expect the introduction of ridesharing to have affected not only the pace of entry into the Taxi and Limousine Services industry but also the likelihood of workers combining earnings from driving with wage and salary earnings. In addition, we hypothesize that the arrival of ridesharing should have made driving a more attractive option for workers displaced from their jobs. Our second set of research questions address the effects of ridesharing on the incumbent taxi and limousine driver workforce. All else the same, rideshare competition should have increased the rate of exit of incumbent drivers from the industry and reduced average incumbent driver earnings. To the extent that the availability of ridesharing apps increased the demand for driving services, however, these effects could have been ameliorated or even possibly reversed.

In addressing these research topics, we explore how differences in pre-existing taxi regulation across local labor markets—specifically, regulations that limited the number of taxis on the road—influenced the effects of interest. We hypothesize that the growth in entry following the introduction of ridesharing should have been larger in labor markets with more stringent taxi regulations, but that the effects on incumbent driver exits and earnings could have been either larger or smaller than the effects in unregulated markets—larger if we are right that the supply of driving services increased more in those markets and the effects of this supply increase were not offset by similar or greater increases in demand, but possibly smaller if supply was not affected in the way we hypothesize or ridesharing produced larger increases in demand in the more regulated markets.

Our analysis rests on comprehensive tax records that allow us to observe both self-employment and wage and salary employment. We integrate longitudinal person-level information on the universe of U.S. sole proprietors who do business on their own with longitudinal information on wage and salary earnings for the universe of employees covered by state unemployment insurance systems. Then, we augment these matched administrative data with information on individuals' gender, age, race, ethnicity, and foreign-born status. The unemployment insurance wage records allow us to identify displaced wage and salary workers, defined as employees who left an establishment at which a large quarter-over-quarter decline in employment occurred during the year of their exit.

The forcing event in our analysis is the entry of rideshare services to a local labor market. Uber is the dominant ridesharing player. Drawing on information from multiple sources, we have identified the date of Uber's entry to each of the metropolitan areas represented in our data set. Variation in whether and when online platform ridesharing became available in different metropolitan areas allows us to quantify the effects of its entry on the outcomes we study. We also have compiled information on the presence of regulations limiting the number of taxis on the road for these same metropolitan areas. This allows us to estimate the influence of these regulations on the relationship between the entry of ridesharing and the outcomes of interest. Because of the stringent requirements New York City imposes on rideshare drivers, we treat the New York City metropolitan area as a special case.

The paper contributes to the existing literature in several ways. First, building on the comprehensive data infrastructure we have developed—an infrastructure that includes information on the earnings and demographic characteristics of everyone working in the industry as a sole proprietor who does not have employees in each year of our study period—we are able to paint a more definitive picture of how ridesharing transformed the Taxi and Limousine Services industry than has been possible in previous research based on convenience samples or survey data. Second, because our longitudinal data infrastructure allows us to track the later labor market experiences of individuals who had been working in the Taxi and Limousine Services industry prior to the introduction of ridesharing, we also are able to show how the arrival of rideshare platforms affected these incumbent drivers. Third, to our knowledge, ours is the first study to explore how taxi industry regulation moderated or exacerbated the effects associated with the introduction of rideshare apps.

II. Background

While still a small fraction of total employment, platform work grew rapidly during the 2010s. Driving services accounted for the lion's share of this growth (Abraham et al. 2019; Farrell, Greig and Hamoudi 2018; Garin, Jackson and Koustas 2022). The introduction of ridesharing offers an interesting case study of an industry that was profoundly affected by the development of platform technology.

Whether platform work is good or bad for workers has been hotly debated. Those performing platform work typically lack employer-provided benefits and do not enjoy the protections afforded to wage and salary workers under U.S. employment law (Abraham and Houseman 2021). On the other hand, many workers value the flexibility afforded by a platform. The most common reason for choosing to drive for Uber given by a sample of 601 drivers surveyed in 2014, was "to earn more income to better support myself or my family" (cited by 91% of respondents), but the three next most common reasons were "to be my own boss and set my own schedule" (87%); "to have more flexibility in my schedule and balance my work with my life and family" (85%); and "to help maintain a steady income because other sources of income are unstable/unpredictable" (74%) (Hall and Krueger 2018). Econometric estimates suggest that platform workers accrue a substantial surplus from being able to work when they want (Chen et al 2019; Chen et al 2020; Angrist, Caldwell and Hall 2021).

Previous research has shown that many drivers are active on the Uber platform only for a short time (Farrell and Greig 2016b; Farrell, Greig and Hamoudi 2018; Hall and Krueger 2018). At least in part, this reflects the use of platform earnings to smooth fluctuations in earnings from a wage and salary job (Farrell and Greig 2016a; Koustas 2018, 2019; Jackson 2022).

An important unanswered question about the growth of rideshare apps is how their introduction affected the incumbent taxi driver workforce. We know of one study that attempted to address this issue. Berger, Chen and Frey (2018) use American Community Survey (ACS) data to look at how Uber entry affected the wages and employment of workers in the Taxi Drivers and Chauffeurs occupation in the 50 largest U.S. metropolitan areas. They report estimates both for everyone with a main job in the occupation and then, to exclude rideshare drivers, at estimates for just wage-earning workers. Because the all-driver estimates fold together incumbent drivers and drivers who entered after ridesharing was introduced, they can't be interpreted as estimates of the effects on incumbent drivers. The models for wage-earning workers exclude rideshare drivers, but they also exclude the majority of incumbent drivers.[1] An additional issue is that, according to Occupational Employment and Wage Statistics (OEWS) data, the majority of wage employees in the Taxi and Limousine Driver *occupation* do not work in the Taxi and Limousine Services *industry*.[2] A final concern with these estimates is that household survey responses commonly suffer from errors in reported employment status and earnings (see, for example, Bound, Brown and Mathiowetz 2001; Abraham et al. 2013). Using comprehensive administrative data to follow incumbent drivers over time, we can look directly at how the introduction of rideshare apps affected individuals who were already working in the Taxi and Limousine Services industry prior to their arrival.

The extent to which the introduction of rideshare platforms alters a local labor market will depend in part on the difficulty of obtaining similar work absent access to a platform. Most jurisdictions have licensing and other requirements for potential taxi drivers, but regulations that limit the number of taxis in service also may be a barrier to working as a taxi driver. The argument for regulating taxi numbers is that free entry leads to oversupply of taxis, producing long driver wait times and low driver incomes (Schaller 2007). Arguments against entry restrictions include the resulting risk of regulatory capture and anti-competitive practices in the

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[1] Occupational Employment and Wage Statistics data show that in 2010, prior to the advent of rideshare apps, there were about 42 thousand wage and salary drivers in the Taxi and Limousine Services industry, far fewer than the roughly 163 thousand nonemplyer sole proprietors in the industry that same year.

[2] OEWS data for 2012, the midpoint of the Berger, Chen and Frey study period, show that 54% percent of wage and salary workers in the Taxi Drivers and Chauffeurs occupation did not work in the 3-digit NAICS industry that includes Taxi and Limousine Services..

industry (Farren, Koopman and Mitchell 2016). Historically, the number of taxis per thousand residents has been markedly lower in large cities that regulate taxi entry than in those that do not (Frankena and Pautler 1984) and taxi deregulation in the early 1980s commonly led to the entry of new taxi firms providing additional taxi capacity (Teal and Berglund 1987). These results suggest that we might expect the introduction of ridesharing to have had a larger effect on driver entry in cities with regulated taxi markets. We know of no prior evidence on differences related to taxi regulation in the effects of ridesharing on driver entry or other labor market outcomes.

III. Data and Measurement

We use the microdata underlying the Census Bureau's published nonemployer statistics to analyze the transformation of NAICS 4853, the Taxi and Limousine Services industry, during the years following the introduction of ridesharing. This is the industry where drivers for taxi, limousine and rideshare companies who file tax returns should be expected to report their self-employment earnings. The Census Bureau defines a nonemployer business as a business that has no paid employment or payroll, is required to file a federal income tax return, and has business receipts of $1,000 or more ($1 or more for the Construction sector). The great majority of nonemployers are self-employed individuals operating as unincorporated sole proprietors, but there also are nonemployer businesses organized as corporations, S-corporations and partnerships. The nonemployer statistics are based on Schedule C's (for unincorporated sole proprietors) and other tax forms providing similar information filed with the Internal Revenue Service (IRS).[3]

Our analysis makes use of data for the years 2010 through 2016. Beginning our analysis with data for 2010 allows us to identify people who were working as traditional taxi or limousine drivers prior to the advent of ridesharing and observing the industry through 2016 allows us to observe how it changed over the period of its most rapid proportional growth. Investigating the impacts of the ridesharing transformation over

[3] The U.S. Census Bureau publishes counts of nonemployers and their receipts at https://www.census.gov/programs-surveys/nonemployer-statistics.html. Since the official nonemployer statistics generally are restricted to individuals with business receipts of at least $1,000, those with the most limited self-employment activity—for example, individuals who try ridesharing but decide after a small number of rides that it is not for them—are excluded.

a longer period also would be of interest, but creating the internally consistent post-2016 data infrastructure needed to do so would be challenging and is beyond the scope of the present paper.[4]

Because we need to be able to identify the individuals to whom each nonemployer business belongs rather than simply that a business exists, we focus on nonemployer sole proprietors. Each sole proprietor record contains the industry in which the business operates; information on gross receipts, expenses and net receipts as reported on the business's Schedule C; and a unique identifier for the business owner, the Census Bureau's Protected Identification Key (PIK).[5] The availability of a PIK for sole proprietors allows their data to be integrated with other administrative data.[6] Some people file multiple Schedule C's (i.e., have more than one business). As a first step in preparing the nonemployer microdata for analysis, we collapse the data, based on the PIK, to one record per individual per year, such that each record contains information for all the businesses a person may have operated in that year. We restrict the sample to those with valid PIKs and delete as outliers cases with the top 0.1% of values for combined business receipts or combined business expenses, which in all cases were implausibly high. In some analyses, we use the 2009 nonemployer data to identify people who were working in the Taxi and Limousine Services industry in 2010 before the advent of ridesharing.

[4]Because of ongoing changes in the content and structure of the multiple administrative data files underlying our analysis, the process of integrating them is complex and each year of data added poses distinct challenges. We also are concerned that, beginning in 2017, many large platform companies stopped voluntarily reporting drivers' receipts to the IRS, instead filing reports only when a driver's receipts exceeded the $20,000 threshold for required reporting. This appears to have had a significant effect on reporting of platform workers' earnings (Garin et al. 2025) and thus presumably on the nonemployer data. A smaller additional issue is that the wage record data needed for a portion of our analysis are missing for selected states in later years.

[5] In principle, most people with any significant net earnings from driving should file both a Schedule C, Profit or Loss from Business (Sole Proprietor), and a Schedule SE, Self-Employment Tax; in practice, the growth in the number of Schedule C filings since 2010 has been substantially greater than the growth in the number of Schedule SE filings. In part, this reflects the fact that, while sole proprietors with any gross receipts are required to file a Schedule C, only those with net earnings of $433 or more are required to file a Schedule SE. This may be important for people working in the Taxi and Limousine Services industry since expense allowances for mileage are very generous. In addition, even among those with positive net earnings of more than $433 reported on a Schedule C, a nontrivial percentage do not file a corresponding Schedule SE (Abraham et al. 2023). The reasons for this discrepancy merit further investigation, but our analysis here relies on the more inclusive Schedule C's.

[6] Information on business owners is less readily available for nonemployer businesses organized as corporations or partnerships. Beginning in 2007, K-1 filings contain information on business ownership, but this information has notable limitations (Goldschlag, Kim and McCue 2017). For our purposes, because essentially all of the growth in nonemployers in NAICS 4853 has been among sole proprietors, restricting our analysis to that group is not a serious limitation.

Using the PIK of the business owner as a linking variable, we supplement the nonemployer microdata with information for the same years on wage and salary earnings from the Longitudinal Employer-Household Dynamics (LEHD) program. The LEHD data are sourced from state Unemployment Insurance (UI) administrative records and cover all private sector employers subject to state UI coverage (approximately 98% of private sector employment), plus state and local government. Federal government employees are the major omitted group of wage and salary earners. The LEHD contains quarterly information on wage and salary earnings for individuals in all 50 states plus the District of Columbia for each year from 2010 through 2016, with the exception of data for Alaska in the second half of 2016.

The final step in creating our core data infrastructure is to incorporate demographic information from the Census Bureau's Individual Characteristics File (ICF). The ICF includes a record for everyone who has ever applied for a Social Security Number (SSN). The information on the ICF includes gender, date of birth, race, Hispanic origin and place of birth plus more limited information about education.[7] In merging the nonemployer data with the ICF information, we exclude nonemployers for whom gender, date of birth, race, ethnicity or place of birth are missing. We restrict our sample to individuals who, based on their birth dates, are 14 to 99 years old in a given year. As shown in Appendix Table B-1, for the years included in our analysis, our final sample includes 93.1% to 94.9% of all nonemployer sole proprietors and 93.3% to 95.8% of NAICS 4853 nonemployer sole proprietors, depending on the year. In both cases, the trend in the number of nonemployer sole proprietors in our analytic sample is very similar to the trend in the published numbers.

By linking individuals' nonemployer records over time, we are able to identify all of the drivers who entered the Taxi and Limousine Services industry in each of the years from 2011 through 2016, where a year *t* entrant is anyone with nonemployer earnings in year *t* for whom we do not observe year *t-1* earnings. This allows us to look at how the characteristics of drivers entering the industry changed after ridesharing began to spread. Next, we estimate models to quantify how the rate of driver entry was affected by the introduction of ridesharing in a local labor market. To estimate these models, we first identify the population at risk of entry, which we define to include anyone age 14 to 99 living in the United States in year *t* for whom we do

[7] The education variable on the ICF is imputed for about 80% of individuals and missing for about another five percent.

not observe prior year NAICS 4853 nonemployer earnings. Our source for identifying the U.S. resident population is the Census Bureau's Resident Candidate File (RCF) or its predecessor, the Composite Person Record (CPR). For most but not all of the resident population, these files include demographic information from the ICF. The RCF or CPR also tells us each person's state and county of current residence, which we use to determine whether the individual lives in a Core Based Statistical Area (CBSA) and, if so, which metropolitan or micropolitan CBSA that was.[8]

Displaced workers are a group of particular interest, as losing a wage and salary job may push a worker into ridesharing or other nonemployer self-employment. Using quarterly earnings data from the LEHD, we identify individuals who experienced a displacement event during the prior year, defined as a separation from an employer at which there was a quarter-over-quarter decline of 50 or more employees that represented at least a 30% decline in employment in any of the four quarters of the year.

Having linked data also allows us to examine the exit of incumbent drivers from the industry. For this purpose, we deem anyone who had NAICS 4853 nonemployer sole proprietor earnings in 2009 and was still working in the industry in 2010 to be a 2010 incumbent.[9] We are able to identify exits from among this 2010 incumbent population in each year from 2010 through 2015, where a year *t* exiter is anyone who had nonemployer earnings in year *t* but not year *t+1*. We also are able to use the information from the nonemployer files on self-employment earnings (receipts minus expenses) and from the LEHD on wage and salary earnings to study changes in the earnings of incumbent drivers over time. [10] Earnings are measured in constant 2015 dollars.

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[8] A CBSA is a geographic area consisting of one or more counties (or equivalents) anchored by an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center by commuting. To qualify as a metropolitan CBSA, the Census Bureau-defined urban cluster must have at least 50,000 people. Micropolitan CBSAs are based on smaller urban clusters with10,000 to 49,999 people.

[9] Although the Census Bureau's published nonemployer estimates for 2009 are slightly larger than our estimates based on the underlying microdata, we can be sure that everyone who had NAICS 4853 nonemployer earnings in the microdata in both 2009 and 2010 was a 2010 incumbent and thus had been working in the industry prior to the introduction of ridesharing. We cannot be sure, however, that everyone we first observe with nonemployer earnings from driving in 2010 was a new entrant. For this reason, our analysis of entrants begins with 2011 entrants while our analysis of exits begins with 2010 exiters.

[10] Nonemployer earnings, defined as receipts minus expenses, are similar but not strictly comparable to wage and salary earnings. On the one hand, a self-employed nonemployer may have the flexibility to deduct common expenses from her receipts, thereby reducing measured net earnings in a way that a wage and salary work cannot. On the other hand, both

In a more speculative analysis, we use reported expenses to construct a rough estimate of miles driven, which we think of as a proxy for work effort. In determining their net taxable earnings, Taxi and Limousine Services drivers may deduct the costs of operating their vehicles, along with any fees paid to a taxi or ridesharing company plus items such as tolls and parking charges (H&R Block 2016). Vehicle operation costs may be determined either by applying the Internal Revenue Service (IRS)-approved mileage rate, which varied between 51.0 and 57.5 cents per mile from 2011 through 2016, or on actual expenses. For this part of our analysis, we proxy miles driven with a measure calculated as driver expenses divided by the IRS mileage rate.

Our main objective is to better understand how the introduction of ridesharing affected the Taxi and Limousine Services industry. We use the year of Uber entry to a local labor market as the year when ridesharing became available. Although there are other rideshare companies, the entry of the Uber platform is a good indicator of the availability of online rideshare platforms more generally.[11] We consider Uber to have entered a market in a calendar year if it began operations by June 30; if operations began after June 30, we code entry as having occurred in the following year. As described more fully in Appendix A,we carried out an exhaustive search of multiple sources of information to identify the Uber entry date for all of the metropolitan CBSAs within existing Uber service areas and all of the micropolitan CBSAs in Uber service areas that do not include one or more metropolitan CBSAs. Our baseline specifications include a linear years-since-entry variable based on these dates.

We also are interested in how regulations restricting driver entry to the taxi industry affect the impact of ridesharing on local labor markets. To explore these issues, we construct an indicator variable for whether a CBSA's core city limits the number of taxis on the road through a medallion or other system. The majority of the largest cities have such systems (for example, Los Angeles, New York and Chicago), but others do not

the employer and the employee portion of payroll taxes must be paid on any net nonemployer earnings. Because relatively few 2010 incumbent taxi drivers moved into wage and salary work as a result of the introduction of ridesharing, the conceptual differences between the two earnings measures is not a major issue for our earnings analysis.

[11] In September 2013, for example, Uber operated in 20 cities while Lyft operated in 10 cities that were a subset of those in which Uber operated.

(for example, Washington, DC, Phoenix and Minneapolis). Regulations restricting taxi entry are much less common in smaller cities.

Our expectation that the presence of taxi regulations might alter the effects of ridesharing in a local market assumes that the introduction of ridesharing significantly lowers the barriers to entry for potential drivers. This appears to have been less true in New York City than in other cities with regulated taxi markets. Over our study period, rideshare drivers in New York City were required to have a Taxi and Limousine Commission (TLC) driving license, meaning that they had to have completed a defensive driving course, a Wheelchair Accessible Vehicle course, and a 24-hour driver education course; passed an exam on the material covered in the driver education course; passed a drug test; gotten fingerprinted; and passed a TLC medical exam. In addition, the vehicles used by New York City rideshare drivers were required to be licensed as commercial vehicles.[12] Given the stringency of the requirements imposed on New York City rideshare drivers, our models allow the effects of Uber entry to be different in New York than in other cities with regulations that limited the number of taxis.

IV. Entry and Growth in the Taxi and Limousine Industry Workforce

Figure 1 depicts the number of metropolitan CBSAs that Uber entered each year from 2011 to 2019, where year of entry is as defined above, and the average population of those markets. After starting with entry into two very large CBSAs in 2011, Uber entered 7 CBSAs in 2012, 10 in 2013 and 51 in 2014, a cumulative total of 70 metropolitan CBSAs. Entry occurred in the largest markets first, but the average population size in new markets remained above a million people through 2014. Over the next five years, Uber expanded into an additional 260 smaller metropolitan CBSAs.[13]

Figure 2 displays the total number of NAICS 4853 nonemployer businesses for each year from 1997 through 2019 and the number organized as sole proprietorships starting in 2008. After trending slowly

[12]The TLC paused licensing of most new for-hire vehicles in 2018 and additional rules regarding rideshare drivers were introduced in 2019, but these restrictions did not apply during our sample period.
[13] As discussed in the data appendix, there are 21 small metropolitan CBSAs in which we believe Uber was operating as of the end of 2019 but for which we could not determine an entry date. These are not reflected in Figure 1.

upwards from 1997 through 2013, the number of nonemployers in this industry shot up sharply beginning in 2013. Almost all of these nonemployer drivers—more than 93% in 2013 and more than 98% by 2019—were unincorporated sole proprietors. The number of nonemployer sole proprietor drivers was more than three times as large in 2016 and more than six times as large in 2019 as in 2013. As shown in Appendix Figure B-1, the number of non-employer businesses outside of NAICS 4853 also grew during this period, but the number of nonemployer sole proprietors was only 6 percent larger in 2016 and 13 percent larger in 2019 than in 2013. Nonemployer statistics are published for only a subset of 4-digit NAICS industries, but as discussed by Abraham et al. (2019), the rate of nonemployer growth in NAICS 485, the three-digit industry that includes NAICS 4853, far exceeded the growth in any other 3-digit industry during this period.

One question about the NAICS 4853 nonemployer data is how they compare to other data on growth in employment in the Taxi and Limousine Services industry. The CPS should in principle capture this growth, but there is considerable evidence that self-employment is underreported in the CPS (Katz and Krueger 2019; Abraham, Haltiwanger, Sandusky and Spletzer 2021; Abraham, Haltiwanger, Hou, Sandusky and Spletzer 2021) and the CPS data capture little of the growth in NAICS 4853 self-employment reported in tax data over the period we study (Abraham et al. 2019).[14] In contrast, the number of drivers listed in Uber's administrative records grew more rapidly than the number of NAICS 4853 nonemployers. Hall and Krueger (2018) report that, by December 2015, there were approximately 463 thousand Uber drivers with four or more trips during the month. By comparison, the number of NAICS 4853 nonemployers rose from approximately 176 thousand in calendar year 2010 to 480 thousand in calendar year 2015, an increase of 304 thousand or about two-thirds the size of the growth in the Uber workforce. Given that the nonemployer data capture drivers who worked at any time during the year whereas the Uber data capture only drivers who worked during a given month, if all of the growth in the Uber workforce represented net new entry to the industry, one would expect the change in the number of nonemployers to be larger, not smaller, than the Uber numbers. Working in the other direction, however, is that growth in the use of the Uber platform at

[14] Jackson, Looney and Ramnath (2017), Collins et al. (2019) and Lim et al. (2019) also document increases in self-employment in tax data more generally that are inconsistent with trends in CPS self-employment.

least partly reflects substitution of work as an Uber driver for work as a traditional taxi or limousine driver, a shift that would raise the number of Uber drivers but not the total number of NAICS 4853 nonemployers. In addition, some drivers on the Uber platform do not meet the $1,000 gross receipts threshold to qualify as a nonemployer business. Tax noncompliance or misreporting also could be a source of divergence between the Uber numbers and the NAICS 4853 nonemployer numbers, but, through 2016, most large platform companies voluntarily reported earnings on their platforms to the IRS (Garin et al. 2025) and tax compliance generally is high for earnings with associated information returns (Internal Revenue Service 2019). The differences between the Uber and nonemployer numbers notwithstanding, the pattern of growth in the nonemployer data seems broadly consistent with that in the Uber administrative data.

The four panels of Figure 3 show selected characteristics of the nonemployer sole proprietors working in NAICS 4853. In each panel, the dark blue bar at the left refers to drivers who earned income as a NAICS 4853 nonemployer sole proprietor in both 2010 and 2011. The lighter blue bars refer to drivers who entered the industry in the years from 2011 through 2016. In every year, new entrants to NAICS 4853 are more likely than the 2011 incumbents to be young (Panel A), female (Panel B), White (Panel C) and native-born (Panel D). It is not surprising that the characteristics of entrants and incumbents are different; one would expect, for example, entrants generally to be younger. Starting in 2013, however, as app-based ridesharing services spread, the characteristics of NAICS 4853 entrants began to change, suggesting that platform-based work was attracting people who would not otherwise have entered the industry. Between 2013 and 2016, the share of new entrants to the NAICS 4853 nonemployer workforce who were under age 35 rose from 33% to 40%; the share who were female from 15% to 25%; the share who were White from 46% to 58%; and the share who were native-born from 31% to 58%.[15] In contrast to the marked changes in

[15] Hall and Krueger (2018) report that the shares of Uber drivers responding to their 2014 survey who were young, female and White exceeded the shares of taxi drivers with the same characteristics in 2012-2013 American Community Survey data. As explained in the text, even absent Uber's entry, we would not necessarily expect the characteristics of entrants to match those of incumbent drivers. Our data allow us to document changes in the demographic composition of entrants to the Taxi and Limousine Services industry over the period of ridesharing's introduction and growth.

the composition of the entrants to NAICS 4853, the demographic characteristics of nonemployer entrants in other industries, shown in Appendix Figure B-2, were little changed over the 2011-2016 period.[16]

The first two panels of Figure 4 display the gross receipts and net earnings of the 2011 NAICS 4853 nonemployer incumbents and of 2011-2016 entrants to the industry. NAICS 4853 incumbents had net earnings from driving that averaged just $12,290 (in 2015 dollars) in 2011. Unsurprisingly given that they are both less experienced than the incumbents and less likely to have worked a full year, the 2011 entrants earned substantially less than the 2011 incumbents, with net earnings of just $7,190.[17] Beginning in 2013, however, the net earnings of NAICS 4853 entrants begin to fall off sharply. By 2016, the average NAICS 4853 entrant had net earnings of just $2,110. As can be seen in Appendix Figure B-3, nonemployer entrants in other industries earned less than incumbents in 2011, but their earnings exhibited no particular trend from 2011 through 2016.

The large difference between the receipts of NAICS 4853 nonemployers (Panel A) and their net earnings (receipts minus expenses, Panel B) implies a high ratio of expenses to receipts for these drivers. In 2016, for example, average expenses among drivers entering NAICS 4853 ($8,360) were almost 80% as large as average receipts ($10,460). By comparison with NAICS 4853, average 2016 expenses for nonemployers entering other industries, shown in Appendix Figure B-3, were under half of average receipts.

Panel C of Figure 4 shows the share of NAICS 4853 nonemployer sole proprietors combining self-employment income with wage and salary income. This is considerably more common among entrants, who typically work for just a part of the year, than among incumbents but once again, the pattern changes after ridesharing began to spread. In 2013, 52% of entrants combined self-employment income with wage and salary income during the year; by 2016, 75% of entrants did so. As shown in Appendix Figure B-3, no such change occurred among nonemployer sole proprietors entering other industries. Moreover, among NAICS 4853 entrants who combined income from driving with wage and salary income, the share for whom net

[16] The numbers underlying all of these figures are reported in Appendix Tables B-2A and B-2B.

[17] Since entry as a nonemployer may occur at any point during the year, most entrants do not work a full twelve months. Incumbents may work a partial year in the year they exit, but the modest exit rates documented later in the paper imply that entrants are much more likely than incumbents to have worked a partial year.

earnings from driving represented a quarter or more of their total earnings (net earnings from driving plus wage and salary income) fell from 47.5% in 2011 to 19.2% in 2016.

Taken together, the decline in average nonemployer earnings and the increased propensity to combine nonemployer self-employment with a wage and salary job among NAICS 4853 entrants are consistent with earlier findings that many app-based drivers use driving to supplement or smooth their earnings rather than as a primary source of income (Farrell and Greig 2016b, Koustas 2018).

The baseline estimating equation for our more formal analysis of how the introduction of ridesharing affected entry into Taxi and Limousine Services is:

$$(1) \qquad ENTER_{it} = \alpha * YEAR_{it} + \beta * YRSUBER_{it} + \tilde{X}_{it}\tilde{\gamma} + \delta * CBSAGROWTH_{it} + \tilde{CBSA}_{it}\tilde{\lambda} + \varepsilon_{it}$$

We fit this equation using person-year observations for the years 2011 through 2016 on all individuals aged 14-99 not already working in the industry. ENTER equals 100 if a person enters Taxi and Limousine Services as a nonemployer sole proprietor in the given year and otherwise is zero. With this scaling, the estimated model coefficients represent percentage point changes in the entry rate associated with changes in the explanatory variables. YEAR is calendar year; YRSUBER is the number of years Uber has operated in the individual's CBSA; X is a vector of indicator variables for gender, age group, foreign born, non-White, Hispanic and education group, together with indicators for missing demographics; CBSAGROWTH is the percent growth in wage and salary employment in the CBSA from year *t-5* through *t-1* as measured in the LEHD; and CBSA is a vector of CBSA dummies, including a dummy for CBSA missing.[18]

In this model, YEAR captures any underlying trends in entry into Taxi and Limousine Services. After platform-based ridesharing was first introduced in San Francisco, it spread to other metropolitan areas. Familiarity with ridesharing and thus the demand for those services appears to grow in the years following their introduction in a market, meaning that YRSUBER better captures the effects of rideshare entry than a simple indicator for whether Uber has entered as of a particular year.[19] Demographic controls are included to

[18] We dropped nonemployers with missing demographics other than education from our analysis sample, but there were some missing values in the files we used to identify the population at risk of entry.
[19] The use of a simple linear term for years since Uber entered simplifies the estimation of the rich set of interaction terms included in our full specification. We also have estimated quadratic specifications for the entry models shown in

account for cross-group differences in the likelihood of becoming a taxi or rideshare driver. Rideshare companies did not randomly select markets to enter but rather entered the largest CBSAs first. Although there could be underlying differences in self-employment growth rates that are correlated with the availability of online rideshare platforms, the controls included in our models—a full set of CBSA dummies plus a CBSA missing dummy and the variable CBSAGROWTH to capture recent employment trends in an area—should largely control for any such potential effects.

The column (1) model in Table 1 establishes that Uber entry is associated with a significant surge in entry of Taxi and Limousine Services nonemployer sole proprietors. The estimated coefficients imply that, in areas where Uber had not entered, the share of the at-risk population entering Taxi and Limousine Services as a nonemployer grew little if at all. Following Uber's entry in a market, however, the average entry rate rose substantially in each of the next several years.

In the model shown in column (2), we add interactions of YRSUBER with dummy variables for the presence of regulations limiting the number of taxis in the CBSA's core city and for the New York City CBSA. These allow for differing effects of rideshare entry depending on the pre-existing regulatory environment. The coefficient on the interaction between YRSUBER and the regulatory dummy variable is positive, the anticipated sign, but modest in size and not statistically significant. In contrast, the estimated coefficient on the interaction between YRSUBER and the New York CBSA dummy is negative and strongly significant. New York City had pre-existing regulations that limited the number of taxis on the road, but the requirements the city imposed on rideshare drivers also meant that the barriers to becoming a rideshare driver there were notably higher than elsewhere.

In the column (3) model, we allow the effects of ridesharing's introduction to differ with an individual's prior year work experiences. This model adds controls for having wage and salary income, having nonemployer income, and having both wage and salary and nonemployer income in the prior year, together with interactions of these variables plus a dummy variable for not working the prior year with

Tables 1 and 2 and for the incumbent outcome models discussed in the next section of the paper. As discussed below, the conclusions to be drawn from those estimates are generally similar to those for the linear specification.

YRSUBER. In addition, the model includes a variable that captures whether the person experienced a job displacement during the previous year, also interacted with YRSUBER. The coefficient estimates imply that Uber entry raised the probability of entry into NAICS 4853 substantially more for people who had worked in the prior year, especially those with prior year nonemployer earnings but including those who only had prior year wage and salary earnings. Prior to Uber entry, few displaced workers found work in NAICS 4853. Displaced workers in any market could potentially have entered the industry by working as a traditional taxi or limousine driver, but in markets where ridesharing has been introduced, the barriers to entry generally are lower. The estimated coefficients imply that the probability of a displaced worker entering NAICS 4853 increased substantially after Uber began operations in a market.

For comparison with the results for NAICS 4853, in Table 2, we also report results for nonemployer sole proprietor entry into other industries. In these models, the population at risk for entry includes only individuals who did no work as a nonemployer sole proprietor in the previous year.[20] As can be seen in column (1), nonemployer entry outside of NAICS 4853 has trended upwards modestly over time and slightly more so in CBSAs where Uber has entered. The remaining columns show that the effect of Uber's presence on entry into non-NAICS 4853 solo self-employment is unrelated to the city's taxi regulation regime (column 2), but that displaced workers are more likely than others to enter non-NAICS 4853 self-employment and that there was a small proportional increase in that probability following Uber entry (column 3). A possible explanation for the Uber effects on entry into non-NAICS 4853 self-employment is that increasing familiarity with online ridesharing platforms raised awareness of other self-employment opportunities, creating a spillover effect. If so, however, this effect is tiny relative to the mean rate of entry into non-NAICS 4853 self-employment.

To help with visualizing and interpreting the contrasting results between Tables 1 and 2, Figure 5 shows selected estimated effects. To put these effects into context, they are scaled relative to the mean rate of entry into NAICS 4853 (for the Table 1 effects) or into other industries (for the Table 2 effects). The first

[20] This specification is slightly asymmetric with the specification in Table 1 as we exclude individuals with prior year NAICS 4853 earnings from the at-risk group. There are relatively few such workers and excluding them facilitates disclosure avoidance clearance.

three comparisons, based on the column (2) coefficients, imply that each of the first few years following Uber's introduction in a non-regulated city raises the NAICS 4853 entry rate by about 65% relative to the mean entry rate for the industry; the proportional effect in the same set of cities on the entry rate in other industries is less than one percent and statistically insignificant. The estimated effect on NAICS 4853 entry is augmented in CBSAs other than New York City where taxi numbers are regulated; in New York City, however, additional years of Uber operations have *less* effect than elsewhere. Accounting for the base, regulated city and the New York effects associated with years since Uber entry, each additional year of Uber operations is estimated to increase entry into NAICS 4853 in New York City by about 53%, considerably less than the estimated 65% impact in non-regulated CBSAs and estimated 78% impact in regulated CBSAs other than New York City. Not surprisingly, the same variables have a minimal effect in the corresponding entry rate equation in Table 2.

The final two comparisons rest on the column (3) estimates. In CBSAs where Uber has not entered, the proportional effect of displacement on entry as a nonemployer sole proprietor is more than three times as large in other industries as in NAICS 4853. One year after Uber entry, taking into account both the base effect and the years-since-Uber entry effect, displacement is associated with a 23% increase relative to the mean entry rate in the probability of becoming a NAICS 4853 nonemployer versus a 17% increase relative to the mean entry rate in the probability of becoming a non-NAICS-4853 nonemployer; by four years after Uber entry, the corresponding figures are 79% for entry into NAICS 4853 versus 29% for entry into other industries.

One question about these results is whether our linear specification is sufficiently flexible to capture the effects of interest. As a check on the robustness of the results reported in Table 1, we have estimated generalized versions of the column (1) and column (2) models that add the square of years since Uber entry and (for column (2)) its interaction with the regulation and New York City dummy variables. The large standard errors on some of the estimated coefficients in the quadratic models are indicative of the difficulty of distinguishing between linear and quadratic effects in data spanning a short time period. In all of the cases where the coefficients in the linear model are statistically significant, however, the coefficients on the linear and quadratic terms are jointly significant. We use the estimated coefficients from the linear and quadratic models to calculate effects on rates of entry into NAICS 4853 four years after Uber's arrival in a local labor market. As shown in Appendix Table B-3, these effects are generally very similar, with the exception that the dampening effect of being in the New York City CBSA on entry rates is even more pronounced in the quadratic model, such that the estimated coefficients imply no effect on driver entry in New York four years following Uber's arrival.

V. Effects of Ridesharing on the Traditional Taxi and Limousine Driver Workforce

The arrival of ridesharing clearly drew new workers into the Taxi and Limousine Services industry. Less is known about the impact of the ridesharing transition on incumbent drivers. Our data infrastructure allows us to follow drivers who worked in the industry prior to the introduction of rideshare apps and observe what happened to them subsequently. For this purpose, we focus on drivers who worked in Taxi and Limousine Services in both 2009 and 2010. We look first at the exits of incumbent drivers from the industry and, then, for those who continued to work in the industry (possibly as a rideshare driver), at the effects on their earnings and, in a more speculative analysis, their work effort. In addition to estimating the overall effects on exit and earnings, we also look separately at low-earning drivers (those who had positive earnings of less than $12,000 in 2015 dollars in 2010) and high-earning drivers (those who earned $12,000 or more in 2010). The $12,000 threshold splits the group of 2010 incumbents roughly in half.

Table 3 reports on models of exit from the Taxi and Limousine Services industry among 2010 incumbent drivers (those with NAICS 4853 earnings in both 2009 and 2010). The sample for these models consists of worker-year observations for 2010 incumbents who had not previously exited the industry and reported NAICS 4853 nonemployer receipts. The value of the dependent variable for exit in the models is one if a driver had positive receipts in year t but not in year $t+1$ and zero otherwise. The explanatory variables in the model include year; years since Uber entry; an interaction of an indicator for restrictive taxi regulations with years since Uber entry; and an interaction of a New York City CBSA dummy with years since Uber entry, along with all of the additional control variables included in the Table 1 entry models and a full set of CBSA dummies.

The negative and significant coefficient on the year variable in the model for low-earning drivers is consistent with the general finding from other research (e.g., Farber 1999) that turnover rates generally fall with tenure, especially in the early years on a job. The presence of ridesharing in a market raises low-earning drivers' exit rates significantly relative to their baseline exit rate. All else the same, the estimated coefficients imply that, outside of cities with regulated taxi markets, a low-earning incumbent who had not previously exited is 6.6 percentage points more likely to exit in a CBSA where Uber had entered 4 years earlier than in a CBSA where Uber had not yet entered. This effect is about 33% smaller in CBSAs that regulate taxi numbers other than the New York City CBSA and about 80% smaller in the New York City CBSA. In contrast, perhaps because higher-earning drivers are almost by definition more attached to the industry, the baseline exit rates of high-earning drivers do not fall over time nor do these drivers' exit rates appear to be affected by the introduction of rideshare apps in their cities.

In principle, an incumbent driver who leaves NAICS 4853 could find other employment. We also have estimated models similar to those reported in Table 3, but with a dependent variable that captures whether an incumbent driver exits employment altogether as opposed to exiting from work as a NAICS 4853 nonemployer sole proprietor. As shown in Appendix Table B-4, for low-earning drivers, the effects of Uber entry on exit from any employment are somewhat smaller than the effects on exit from NAICS 4853, but otherwise the results are very similar to those reported in Table 3.

Anecdotally, in addition to ridesharing having pushed drivers out of the industry, some incumbent taxi drivers who continued to drive may have suffered significant earnings losses. Table 4 reports estimates of the effects of Uber's presence in a market on earnings (receipts minus expenses) from driving among those who continue to drive, measured in 2015 dollars. An incumbent taxi driver is included in the sample in a given year as long as she had positive gross receipts from driving in that year. Because the sample begins in 2011 (the first year for which we observe a post-2010 change in earnings) rather than 2010 (the first year that exit from the sample may occur), the number of observations in these models is smaller than in the exit models reported in Table 3. As with the exit equations, we differentiate between the effects on low-earning and high-earning drivers. In addition to the variables included in the exit models reported in Table 3, the earnings models include a dummy variable that captures whether the observation is the final year in which a driver had NAICS 4853 earnings; this is important because earnings are mechanically lower if a driver only works for part of the year.

In the first three columns of Table 4, the dependent variable is the change in the level of earnings from driving. Both low-earning and high-earning drivers saw their earnings fall following Uber entry into their local labor market. The estimated coefficients imply that, for a low-earning driver in a city without restrictive taxi regulations where Uber entered four years earlier, annual earnings are a little more than $600 lower than they otherwise would have been; for a high-earning driver, they are about $1,200 lower. In cities with regulated taxi markets other than New York, these effects are erased for low-earning drivers and only about a third as large for high-earning drivers. Perhaps surprisingly, in New York City, Uber entry was associated with somewhat *higher* annual earnings for both groups of drivers.

The final column of the table reports results for high-earning drivers using the percentage change in a driver's real earnings compared to their 2010 real earnings.[21] The estimated coefficients imply that, for a high-earning driver living in a non-regulated city where Uber had entered four years earlier, real earnings are almost 7% lower relative to the driver's 2010 earnings than they otherwise would have been. As in the earnings level change model for the same group, however, this effect is smaller in regulated markets and reversed in New York City.

To the extent that drivers were able to obtain other work to offset the loss of their NAICS 4853 earnings, these estimates could paint an incomplete picture of how the introduction of ridesharing affected incumbent drivers' earnings. Results reported in Appendix Table B-5, however, show that the pattern of change in overall earnings is very similar to that for earnings from driving alone.

A natural question is whether, following the entry of ridesharing, incumbent drivers increased their

[21] Because some low-earning drivers had negative or very small positive amounts of net income from driving, the percentage change results for that group don't have a simple interpretation and we report the percentage change model only for high-earning drivers.

working hours to offset larger reductions in earnings that otherwise would have occurred (see, e.g., Hu 2017). We do not observe drivers' hours, but as described above, we can use reported expenses to generate a crude proxy for miles driven (total expenses divided by the IRS mileage rate). This proxy has notable limitations—vehicle expenses claimed by drivers, especially those who rent their vehicles, may not be based on the mileage rate and drivers' deductible expenses include more than their vehicle costs. As such, this analysis should be regarded as no more than suggestive. Further details regarding the approach, its limitations and the details of our findings are reported in Appendix C; here we summarize the main results.

Keeping the caveats associated with our estimation approach in mind, Uber entry is associated with a statistically significant increase in estimated driver miles. For incumbent drivers in unregulated areas, for example, the estimated coefficient in the model for the full sample implies an increase four years after Uber entry of about 80 miles per week; the estimated impact is somewhat higher for low-earning incumbents and somewhat lower for high-earning incumbents. The estimated percentage impact for the latter group is not statistically significant. Being in a regulated market does not significantly affect these estimates; for incumbent drivers in the New York City CBSA, however, the mileage effects were noticeably smaller. Taken as a whole, these results offer suggestive evidence that, at least outside of New York City, incumbent drivers increased their driving mileage following the introduction of ridesharing. Had they not done so, their earnings might well have been more adversely affected.

As a check on the robustness of the results reported in Tables 3 and 4, we have estimated generalized versions of all of the reported models that add the square of years since Uber entry and its interaction with the regulation and New York City dummy variables. Although the coefficient estimates are somewhat noisy, in every case where the linear model coefficient is statistically significant, the linear and quadratic terms in the generalized models are jointly significant. We use the estimated coefficients from the two sets of models to calculate effects on exits of incumbent drivers from NAICS 4853 and on the earnings of incumbent drivers who do not exit four years after Uber's arrival in a local labor market. These results are shown in Appendix Tables B-6 and B-7. As was true of the entry models, the quadratic specifications generally imply effects that are quite similar to the effects implied by the linear models. One apparent difference is that, in the quadratic models, four years after Uber entry, low-earning incumbent New York City drivers were estimated to be less likely to exit. Another is that, for both high- and low-earning incumbent New York City drivers, Uber entry appears to have raised, not lowered driver earnings.

VI. Conclusion

During the period covered by our analysis, the Taxi and Limousine Services industry (NAICS 4853) stood out not only with respect to the growth in the number of nonemployer sole proprietors following the advent of ridesharing, but also with respect to the changing characteristics of the nonemployer entrants and the nature of their participation in the industry. The people who entered NAICS 4853 after 2013 were increasingly more likely than the taxi and limousine drivers who had been working in the industry prior to the introduction of ridesharing to be young, female, White and U.S. born. Over time, the earnings of new drivers in the industry fell and they became increasingly likely to combine driving with wage and salary work. In contrast, the characteristics of entrants to nonemployer activity in other industries changed little over the years following the introduction of ridesharing. More formal regression analyses show not only that the introduction of ridesharing was associated with a surge of entry into NAICS 4853 but that this effect was larger in the typical city with a regulated taxi market. This was not the case, however, in New York City, a finding we attribute to the relatively stringent entry requirements imposed on New York City rideshare drivers. We also find evidence that working through a rideshare platform is a substantially more attractive option for workers displaced from their jobs than working as a traditional taxi or limousine driver.

The data infrastructure we have developed also allows us to examine the impact of ridesharing on the people who had been working as traditional taxi drivers prior to the introduction of ridesharing. Ridesharing entry into local labor market produced a substantial increase in exits of incumbent drivers from the industry that grew as the rideshare companies become more established, though this increase in exits was concentrated entirely among drivers who had low initial earnings. The increase in exits was weaker in cities with regulated taxi markets and especially so in New York City. Incumbent drivers in areas without restrictive taxi regulations who remained in the industry experienced notable losses in their earnings from driving after rideshare companies arrived in their local labor market and these losses accumulated over time. In contrast, in cities with regulated taxi markets, the introduction of ridesharing appears to have been associated with smaller or no declines in the earnings of incumbent taxi drivers. The effects on incumbent drivers' earnings may have been ameliorated at least to some extent by increases in driver effort, though we are less able to pin down that effect.

This case study of how ridesharing technology transformed the Taxi and Limousine Services industry provides valuable insights for thinking about the potential effects of online platform technology more generally. Both the similarities and the differences in the use of online platform technologies in the ridesharing setting as compared to other settings are relevant to thinking about the generalizability of our findings. An important commonality across different applications of online platform technology is that they have made it easier to match buyers and sellers. In the ridesharing industry, as in food and grocery delivery services, both of which have experienced growth in the post-pandemic economy, this matching occurs in real time. Another important characteristic of the ridesharing platforms is the enormous flexibility that a driver has with respect to the times of day, week, and year that she engages in the activity, again something that they have in common at least with food and grocery delivery services.

In contrast to many other activities that might be mediated through an online platform, an important feature of ridesharing services is that they require direct contact between the seller (driver) and the buyer (passenger). For many other types of work, online platforms could in principle make it possible for sellers (providers) to do their work remotely. There has been considerable discussion of how gig work facilitated by online platforms might broaden the pool of workers available to carry out work and free workers to live where they liked. It remains an interesting open question whether the increased prevalence of remote work more generally in the post-pandemic economy will be accompanied by the long-projected surge in gig activity that involves the remote provisions of goods and services. Growth in gig employment in what effectively would be a national (or even international) labor market rather than, as in the rideshare case, a local labor market could well have effects on workers that differ substantially from those documented here.

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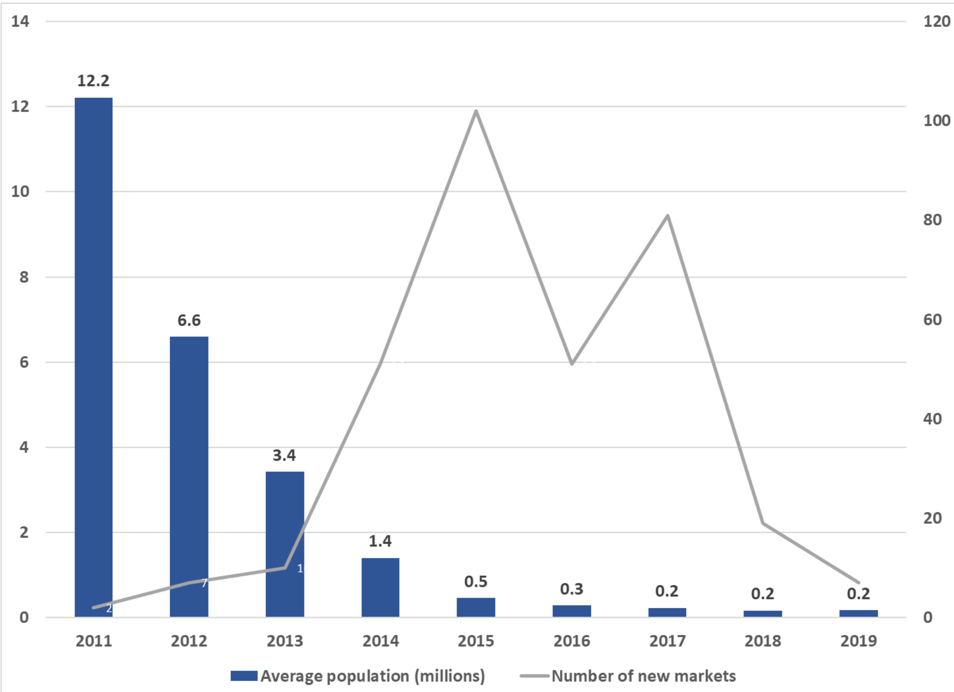
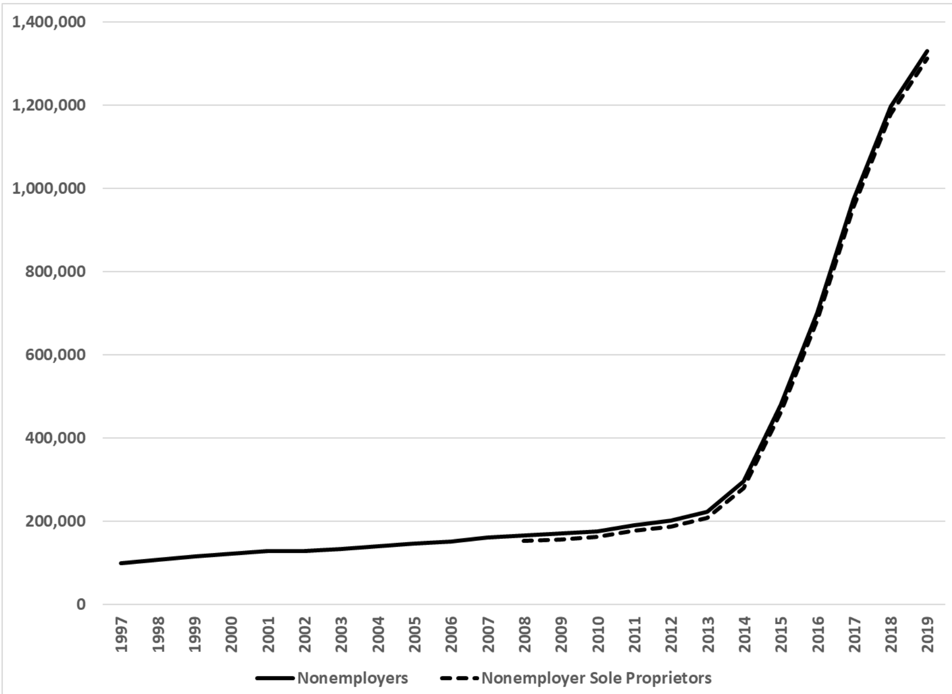
Figure 1: Number and Average Size of Markets Newly Entered by Uber, 2011-2019



Note: A market is defined as a Core Based Statistical Area (CBSA). Date of Uber entry determined by authors based on information supplied by Uber Chief Economist Jonathan Hall and other archival research described in the Data Appendix. Uber considered to have entered a CBSA in a year if operations began by June 30. Average CBSA size based on 2013 Census Bureau population estimates.

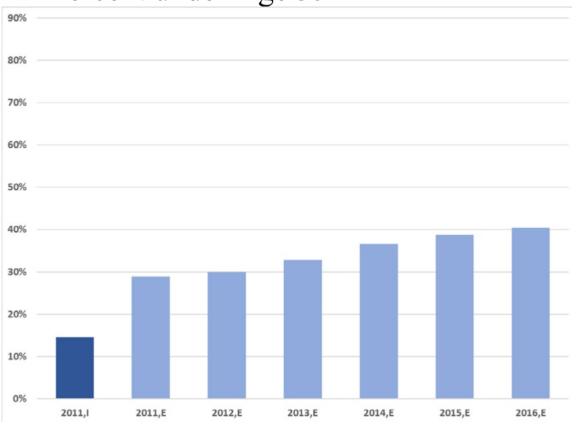
Figure 2: Nonemployer Businesses, NAICS 4853, Taxi and Limousine Services, 1997-2019



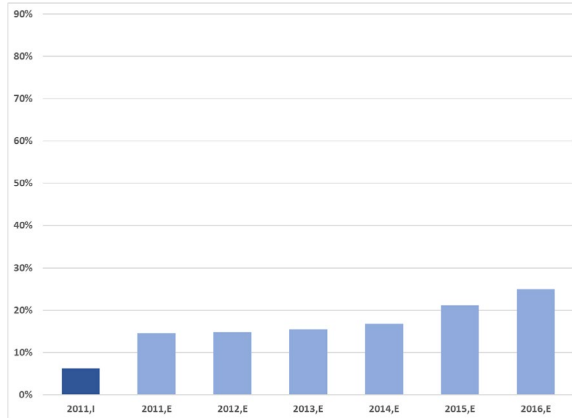
Source: Published Census Bureau nonemployer statistics.

Figure 3: Selected Characteristics of Nonemployer Sole Proprietors in NAICS 4853, 2011 Incumbents and 2011-2016 Entrants

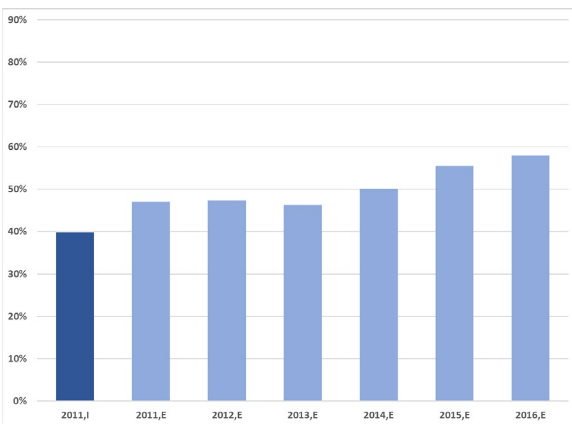
A. Percent under Age 35



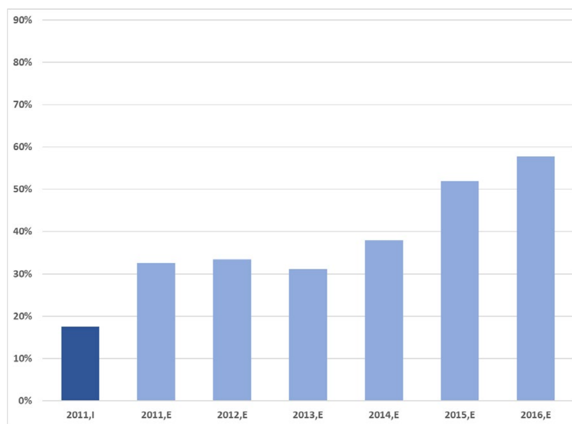
B. Percent Female



C. Percent White



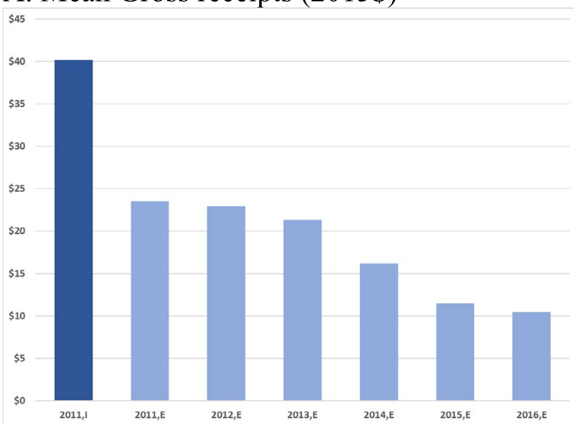
D. Percent Native Born



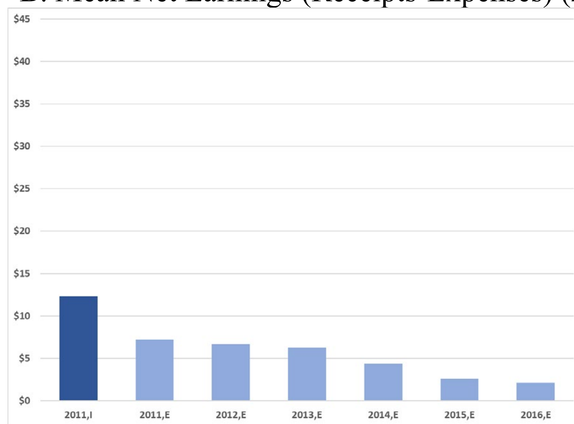
Source: Estimates from authors' calculations based on data infrastructure described in text.

Figure 4: Selected Income-related Measures, Nonemployer Sole Proprietors in NAICS 4853, 2011 Incumbents and 2011-2016 Entrants

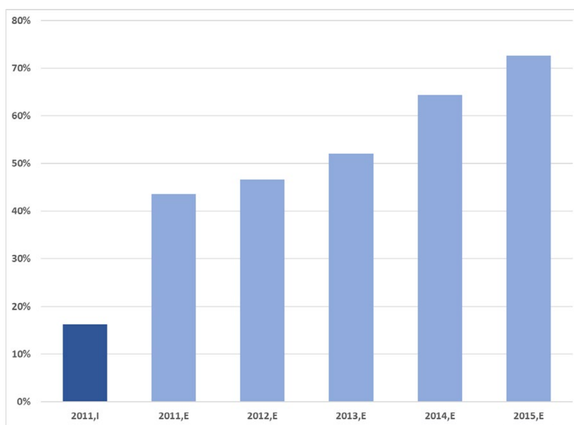
A. Mean Gross receipts (2015$)



B. Mean Net Earnings (Receipts-Expenses) (2015$)

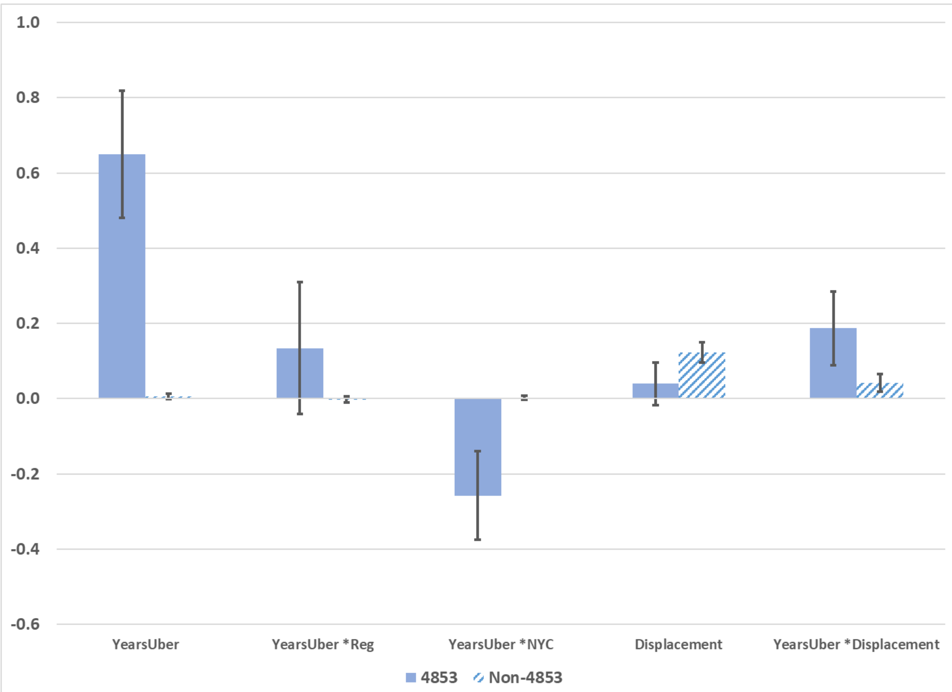


C. Share with Wage and Salary Earnings



Source: Estimates from authors' calculations based on data infrastructure described in text.

Figure 5: Size of Marginal Proportional Effects on Nonemployer Sole Proprietor Entry Relative to Mean Entry Rate, NAICS 4853 versus Other Industries



Source: First three pairs of estimates based on coefficients reported in column (2) of Tables 1 and 2; final two pairs based on coefficients reported in column (3) of the same tables.

Table 1: Uber's Presence in a Market and Nonemployer Entry into NAICS 4853, Taxi and Limousine Services, 2011-2016

			(1)		(2)		(3)	
	Mean	[S.D.]	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Year	2014		0.0010	(0.0019)	0.0018	(0.0017)	0.0018	(0.0017)
YearsUber	1.14	[1.57]	0.0404	(0.0037)	0.0378	(0.0050)		
Years Uber * Regulation	0.79	[1.49]			0.0078	(0.0052)	0.0071	(0.0051)
Years Uber * Regulation * NY CBSA	0.22	[0.96]			-0.0150	(0.0035)	-0.0152	(0.0034)
{0,1} Wage and Salary only last year	0.55	[0.50]					-0.0368	(0.0079)
{0,1} Nonemployer not 4853 only last year	0.03	[0.17]					-0.0721	(0.0569)
{0,1} Both W&S and Nonemployer last year	0.02	[0.15]					-0.0269	(0.0124)
{0,1} Displaced last year	0.03	[0.18]					0.0023	(0.0017)
Years Uber * {0,1} W&S only last year	0.64	[1.31]					0.0452	(0.0056)
Years Uber * {0,1} Nonemployer only last year	0.03	[0.33]					0.1048	(0.0165)
Years Uber * {0,1} Both W&S and Nonemployer las	0.03	[0.31]					0.1538	(0.0181)
Years Uber * {0,1} Not Employed last year	0.44	[1.12]					0.0137	(0.0054)
Years Uber * {0,1} Displaced last year	0.04	[0.36]					0.0109	(0.0029)
R-squared			0.0015		0.0015		0.0019	

Note: Sample is person-year observations for individuals age 14 to 99 at risk for entry as a nonemployer sole proprietor to NAICS 4853, Taxi and Limousine Services, in a given year. Dependent variable=100 if person enters NAICS 4853 in observation year, else=0; mean=0.0582. YearsUber is number of years Uber has been present in a Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0; mean of Regulation=0.3884 and mean of Regulation*NY CBSA=0.0637. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicators for missing demographics; percent employment growth in CBSA from year t-5 through year t-1; 919 CBSA dummies; and CBSA missing indicator. Standard errors clustered at CBSA level. N=1,514,000,000.

Table 2: Uber's Presence in a Market and Nonemployer Entry into Industries other than NAICS 4853, Taxi and Limousine Services, 2011-2016

			(1)		(2)		(3)	
	Mean	[S.D.]	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Year	2014		0.0086	(0.0026)	0.0081	(0.0026)	0.0085	(0.0025)
Years Uber	1.14	[1.57]	0.0137	(0.0057)	0.0161	(0.0090)		
Years Uber * Regulation	0.78	[1.49]			-0.0054	(0.0100)	-0.0055	(0.0103)
Years Uber * Regulation * NY CBSA	0.22	[0.96]			0.0071	(0.0070)	0.0052	(0.0070)
{0,1} Wage and Salary last year	0.58	[0.49]					-0.2539	(0.0459)
{0,1} Displaced last year	0.03	[0.18]					0.2966	(0.0336)
Years Uber * {0,1} W&S last year	0.68	[1.34]					0.0354	(0.0115)
Years Uber * {0,1} Not W&S last year	0.46	[1.14]					-0.0186	(0.0105)
Years Uber * {0,1} Displaced last year	0.04	[0.36]					0.1014	(0.0293)
R-squared			0.0086		0.0086		0.0087	

Note: Sample is person-year observations for individuals age 14 to 99 at risk for entry as a nonemployer sole proprietor to industries other than NAICS 4853, Taxi and Limousine Services, in a given year. Dependent variable=100 if person enters a non-NAICS-4853 industry in observation year, else=0; mean=2.408. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0; mean of Regulation=0.3871 and mean of Regulation*NY CBSA=0.0636. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicators for missing demographics; percent employment growth in CBSA from year t-5 through year t-1; 919 CBSA dummies; and CBSA missing indicator. Standard errors clustered at CBSA level. N=1,435,000,000.

Table 3: Uber's Presence in a Market and Incumbent Exit from NAICS 4853, Taxi and Limousine Services, 2010-2015

	All 2010 incumbents (1)		Incumbents with <$12,000 NAICS 4853 net earnings in 2010 (2)		Incumbents with ≥$12,000 NAICS 4853 net earnings in 2010 (3)	
	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)
Year	2013	-0.0200	2013	-0.0271	2013	-0.0004
		(0.0023)		(0.0030)		(0.0021)
YearsUber	2.13	0.0131	1.88	0.0166	2.39	-0.0008
	[1.87]	(0.0026)	[1.81]	(0.0036)	[1.89]	(0.0025)
YearsUber * Regulation	1.82	-0.0031	1.53	-0.0055	2.12	-0.0003
	[1.93]	(0.0018)	[1.84]	(0.0029)	[1.98]	(0.0016)
YearsUber * Regulation * NY CBSA	1.26	-0.0030	0.95	-0.0077	1.58	-0.0018
	[1.88]	(0.0012)	[1.69]	(0.0018)	[2.01]	(0.0013)
R-squared		0.0348		0.0408		0.0257
Dependent variable mean		0.1269		0.1566		0.0933
N		484,000		248,000		236,000

Note: Sample is person-year observations for individuals who were NAICS 4853 nonemployer sole proprietors in both 2009 and 2010 and remained a NAICS 4853 nonemployer sole proprietor through observation year. Dependent variable=1 if not a NAICS 4853 nonemployer in following year, implying observation year exit, else=0. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; CBSA dummies (778 in model 1, 504 in model 2 and 743 in model 3); and CBSA missing indicator. Standard errors clustered at CBSA level.

Table 4: Uber's Presence in a Market and Changes in Incumbents' Net Earnings in NAICS 4853, Taxi and Limousine Services, 2011-2015

	Net Earnings in t - Net Earnngs in 2010						(Net Earnings in t - Net Earnings in 2010)/ Net Earnings in 2010	
	All 2010 incumbents (1)		Incumbents with 2010 NAICS 4853 net earnings <$12,000 (2)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (3)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (4)	
	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)
Year	2013	84.4	2013	479.6	2013	-379.3	2013	-0.0132
		(65.9)		(53.5)		(92.1)		(0.0041)
YearsUber	1.82	-221.9	1.62	-159.0	2.03	-298.8	2.03	-0.0166
	[1.60]	(65.6)	[1.56]	(53.2)	[1.61]	(103.4)	[1.61]	(0.0054)
YearsUber * Regulation	1.58	127.3	1.33	160.5	1.82	195.7	1.82	0.0136
	[1.66]	(84.8)	[1.59]	(61.0)	[1.69]	(131.3)	[1.69]	(0.0059)
YearsUber * Regulation * NY CBSA	1.12	138.8	0.85	227.3	1.39	332.9	1.39	0.0163
	[1.63]	(76.2)	[1.48]	(53.9)	[1.72]	(110.5)	[1.72]	(0.0045)
R-squared		0.0168		0.033		0.0385		0.0386
Dependent variable mean		-$203		$1,998		-$2,393		-0.0800
N		371,000		185,000		186,000		186,000

Note: Sample is person-year observations for individuals who were NAICS 4853 nonemployer sole proprietors in both 2009 and 2010 and remained a NAICS 4853 nonemployer sole proprietor through observation year. Dependent variables defined based on net earnings in 2015 dollars. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; CBSA dummies (713 in model 1, 674 in model 2 and 457 in models 3 and 4); CBSA missing indicator; and an exit dummy =1 if person exited NAICS 4853 during year, else=0. Standard errors clustered at CBSA level.

Appendix A: Data Sources and Variable Construction

Administrative Data Sources

A description of the Census Bureau's published nonemployer statistics can be found at https://www.census.gov/programs-surveys/nonemployer-statistics/technical-documentation/methodology.html. Davis et al. (2009) discusses the nonemployer microdata.

The data on wage and salary earnings used in our analysis come from the Longitudinal Household-Employer Dynamics (LEHD) data infrastructure and the data on individual characteristics come from the Census Bureau's Individual Characteristics (ICF) file. Both are described in Vilhuber (2018).

Modeling nonemployer entry requires identification of the population at risk for entry, which we define as individuals aged 14-99 who had no NAICS 4853 nonemployer sole proprietor earnings in the previous year (for entry as a NAICS 4853 nonemployer sole proprietor) or who had no nonemployer sole proprietor earnings in any industry in the previous year (for entry as a non-NAICS-4853 nonemployer sole proprietor). For 2012-2016, we identify this population based on the Census Bureau's Resident Candidate File (RCF); for 2010-2011, we use the Composite Person Record (CPR) file (Graham, Kutzbach and Sandler 2017). These files list everyone with a PIK that the Census Bureau has identified as currently resident in the United States and provide a current state and county of residence. This information can be cross-walked to defined Core Based Statistical Areas (CBSAs), allowing us to merge in locality-specific information that might help to explain nonemployer entry, exit or earnings.

Uber Entry Dates

A key variable in our analysis is the year in which Uber entered an individual's local labor market. For our purposes, a local labor market is a CBSA . Metropolitan CBSAs are urban clusters of at least 50,000 people plus counties tied to that cluster through commuting patterns; micropolitan CBSAs are defined similarly, but for urban clusters with a population of between 10,000 and 50,000 people (https://www.govinfo.gov/content/pkg/FR-2010-06-28/pdf/2010-15605.pdf). Because we would expect the effects of Uber entry to be small in the initial months after entry to a local area, we consider Uber to have entered a CBSA in a given year only if it operated there for at least half the year, i.e., if it entered after June 30 of the previous year and by June 30 of the year in question.

To identify the date that Uber entered a metropolitan CBSA, we started with a list of Uber areas provided by Jonathan Hall, Uber Chief Economist, in March 2018, that also included the month and year Uber service began in each area. We updated this list of Uber areas to include additional areas that had been added to the Uber website as of November 2019. At that time, maps showing the current boundaries of the various Uber areas were available on the Uber website at https://www.uber.com/global/en/cities/. Uber areas can be large, sometimes spanning several metropolitan CBSAs, and entry into the metropolitan CBSAs within the current boundaries of an Uber area can occur at different dates. For example, as of November 2019, the Chicago Uber area included not only the Chicago-Naperville-Elgin, IL-IN-WI metropolitan CBSA, where Uber entered in September 2011, but also the Kankakee, IL metropolitan CBSA located some 60 miles away, where Uber did not enter until June 2015. To take another example, as of the same date, the Washington, DC Uber area included not only the Washington-Arlington-Alexandria, DC-VA-MD-WV metropolitan CBSA, where Uber entered in December 2011, but also the Winchester, VA metropolitan CBSA located some 75 miles away, where Uber did not enter until August 2016.

We examined the Uber area maps posted to the Uber website as of November 2019 to identify the metropolitan CBSAs each area included. This produced a list of 351 metropolitan CBSAs that had Uber service as of that date. Next, we searched for evidence on when Uber entered each of these metropolitan CBSAs. Where the name of the CBSA matched the name of an Uber area, absent evidence to the contrary, we accepted the entry date provided on the original Uber list. For other metropolitan CBSAs, we searched Uber press releases, news stories and other sources for positive evidence regarding an Uber entry date. Of the 351 metropolitan CBSAs we identified for which the maps on the Uber website indicated service was available as of November 2019, we were able to establish a documented month and year of Uber entry for 330 CBSAs. Of these, we code 108 CBSAs with Uber entry in 2017 or later (i.e., as having an entry date of July 2016 or later), meaning we do not observe Uber entry during our study period.

The 21 identified metropolitan CBSAs for which we were unable to determine an Uber entry date all are relatively small cities. Only three of these CBSAs—Vallejo-Fairfield, CA, Crestview-Fort Walton Beach-Destin, FL, and Elkhart-Goshen, IN—had populations of 200,000 or more in 2013; the average 2013 population in the 18 remaining CBSAs was just under 140,000. Uber entry into smaller metropolitan CBSAs generally has lagged entry into larger metropolitan CBSAs. The average 2013 population for CBSAs where Uber entered in 2011 was 12.2 million in 2011; for CBSAs entered in 2012, 6.6 million; for CBSAs entered in 2013, 3.4 million; for CBSAs entered in 2014, 1.4 million; for CBSAs entered in 2015, 0.5 million in 2015; and for CBSAs entered in 2016, 0.3 million. As already noted, we consider Uber to have entered a CBSA if it arrived by June 30 of the indicated year. We treat the 21 metropolitan CBSAs for which we could not determine a definitive entry date as not having entered by the end of our sample period.

We attempted to determine Uber entry dates for micropolitan CBSAs included in an Uber area only in cases where the Uber area contained no metropolitan CBSA, such as the Boone, NC and Golden Triangle Uber areas. Following this approach, we identify Uber entry dates for 27 micropolitan CBSAs, but Uber had entered only two of these CBSAs by June 30 of 2016.

Taxi Regulations

Another variable used in our analysis captures whether regulations in a metropolitan area limit the number of taxis on the road through a medallion system or vehicle cap. To create this variable, we obtained information on the regulations in place for the core city of each of the 103 metropolitan CBSAs with a 2013 population of 500,000 or more for which we had an Uber entry date. We did the same for the core city in a random sample of 20 the 254 smaller CBSAs included on our Uber entry list. For each of these cities, we searched online for definitive information regarding the regulatory regime and, if that was not successful, wrote to or called the relevant city office to obtain the information we needed.

Among the 103 CBSAs with a 2013 population of 500,000 or more for which we had an Uber entry date, 31 (30%) had regulations in place in their core city as of early 2020 that limited the number of taxis on the road. This included the core city in 20 of the 29 CBSAs with populations of more than two million (65%), the core city in 7 of the 21 CBSAs with populations between 1 million and 2 million (33%) and the core city in 4 of 51 CBSAs with populations between 500,000 and 1 million (8%). Among the 20 CBSAs with 2013 populations under 500,000 that we checked, none except Key West had regulations limiting the number of taxis and, given its unusual geography, Key West's situation is decidedly anomalous. We code CBSAs that had populations of less than 500,000 in 2013 as not regulating the number of taxis on the road. Taxi regulations change slowly, making it reasonable to use the information from early 2020 to capture the regime in place over our study period. We assign the regulation status for the core city in each larger CBSA to the CBSA as a whole.

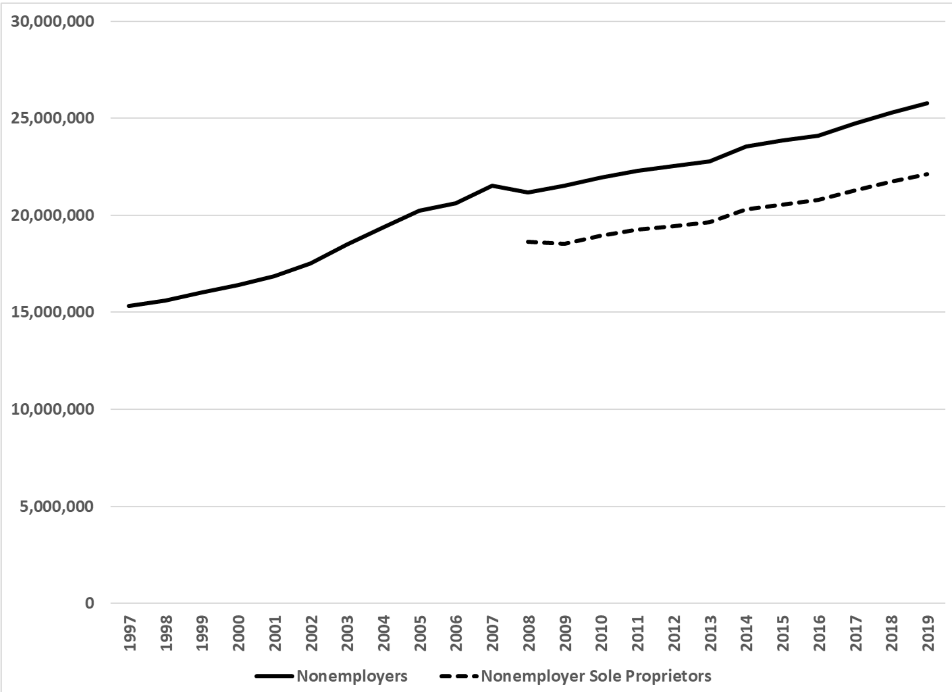
References

Davis, Steven J., John Haltiwanger, Ronald S. Jarmin, C.J. Krizan, Javier Miranda, Alfred Nucci, and Kristin Sandusky. 2009. “Measuring the Dynamics of Young and Small Businesses: Integrating the Employer and Nonemployer Universes,” in T. Dunne, J.B. Bradford and M.J. Roberts, eds., *Producer Dynamics: New Evidence from Micro Data*, Chicago: University of Chicago Press, 329-366.

Graham, Matthew R., Mark J. Kutzbach and Danielle H. Sandler. 2017. “Developing a Residence Candidate File for Use with Employer-Employee Matched Data,” Center for Economic Studies Working Paper No. 17-40, U.S. Census Bureau. May.

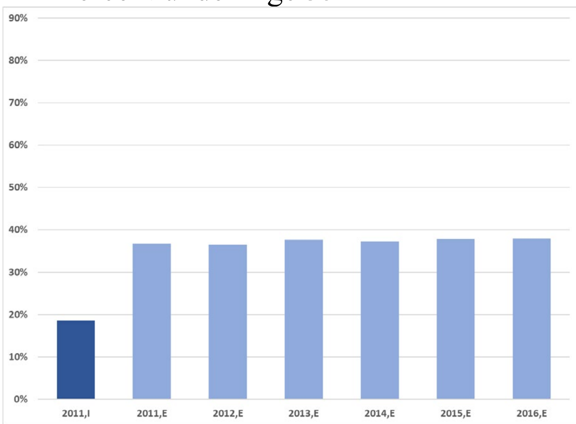
Vilhuber, Lars. 2018. “LEHD Infrastructure S2014 files in the FSRDC,” CES Working Paper CES 18-27R, Census Bureau. September.

Appendix Figure B-1: Nonemployer Businesses, All Industries Excluding NAICS 4853, Taxi and Limousine Services, 1997-2019

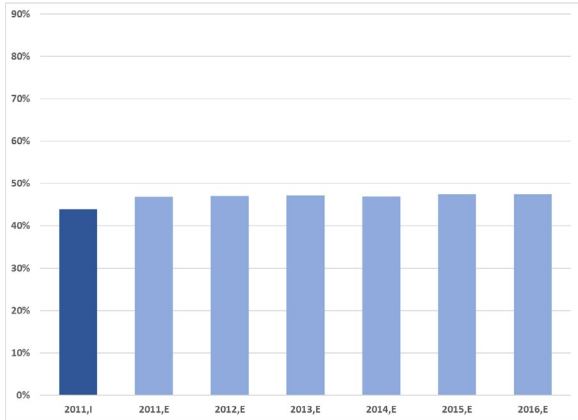


Appendix Figure B-2: Selected Characteristics of Nonemployer Sole Proprietors not in NAICS 4853, 2011 Incumbents and 2011-2016 Entrants

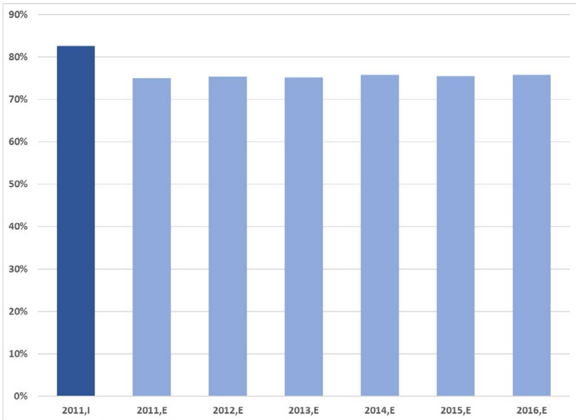
A. Percent under Age 35



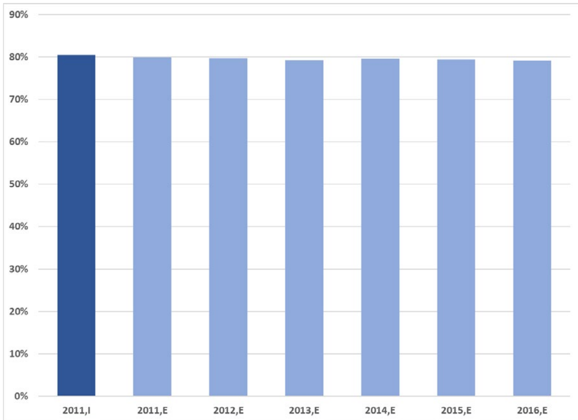
B. Percent Female



C. Percent White



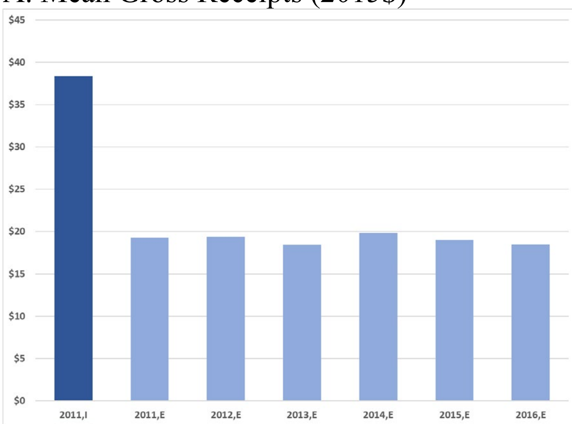
D. Percent Native Born



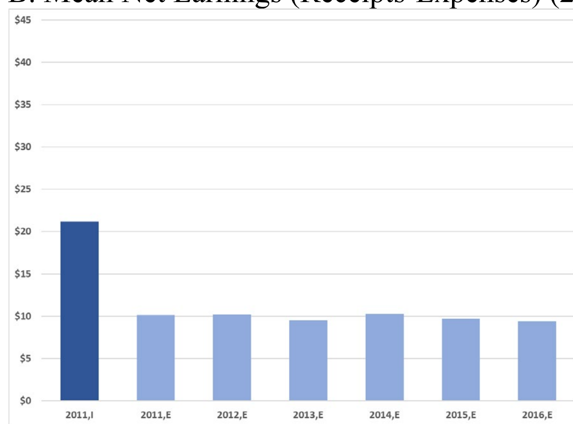
Source: Estimates from authors' calculations based on data infrastructure described in text.

Appendix Figure B-3: Selected Income-related Measures, Nonemployer Sole Proprietors not in NAICS 4853, 2011 Incumbents and 2011-2016 Entrants

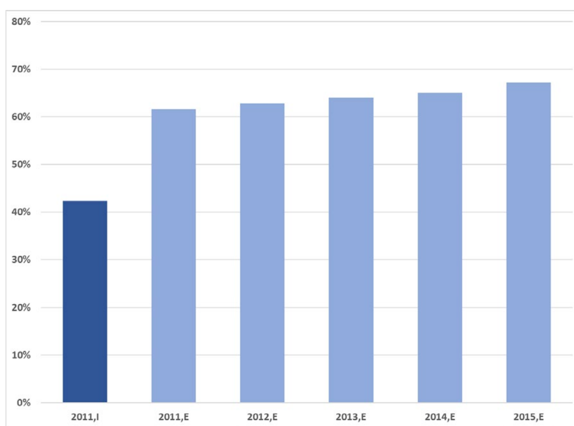
A. Mean Gross Receipts (2015$)



B. Mean Net Earnings (Receipts-Expenses) (2015$)



C. Share with Wage and Salary Earnings



Source: Estimates from authors' calculations based on data infrastructure described in text.

Appendix Table B-1: Nonemployer Sole Proprietors, Published and Analytic Sample

Year	NAICS 4853 Nonemployer Sole Proprietors, Published	Indexed Value (2013=1.00)	NAICS 4853 Nonemployer Sole Proprietors, Analytic Sample	Indexed Value (2013=1.00)
2008	153,628	0.74		
2009	156,905	0.75		
2010	162,732	0.78	156,000	0.79
2011	177,392	0.85	169,000	0.86
2012	187,788	0.90	178,000	0.90
2013	208,692	1.00	197,000	1.00
2014	279,417	1.34	263,000	1.34
2015	462,906	2.22	437,000	2.22
2016	683,135	3.27	638,000	3.24
2017	956,467	4.58		
2018	1,179,167	5.65		
2019	1,312,413	6.29		

Year	All Nonemployer Sole Proprietors, Published	Indexed Value (2013=1.00)	All Nonemployer Sole Proprietors, Analytic Sample	Indexed Value (2013=1.00)
2008	18,808,725	0.95		
2009	18,701,855	0.94		
2010	19,112,075	0.96	18,140,000	0.97
2011	19,438,914	0.98	18,450,000	0.99
2012	19,634,605	0.99	18,540,000	0.99
2013	19,850,941	1.00	18,710,000	1.00
2014	20,592,806	1.04	19,320,000	1.03
2015	21,023,170	1.06	19,690,000	1.05
2016	21,490,556	1.08	20,010,000	1.07
2017	22,247,406	1.12		
2018	22,933,726	1.16		
2019	23,434,804	1.18		

Source: Published Census Bureau nonemployer statistics and authors' calculations.

Appendix Table B-2A: Descriptive Statistics (Means), Nonemployer Sole Proprietors in NAICS 4853: Taxi and Limousine Services, 2011 Incumbents and 2011-2016 Entrants

	Incumbent	Entrants					
	2011	2011	2012	2013	2014	2015	2016
1 if Female	.0625	.1463	.1474	.1547	.1680	.2113	.2498
1 if Age 14-20	.0005	.0080	.0076	.0081	.0076	.0072	.0075
1 if Age 21-24	.0095	.0435	.0459	.0512	.0595	.0725	.0823
1 if Age 25-34	.1363	.2376	.2458	.2694	.2989	.3082	.3147
1 if Age 35-44	.2628	.2744	.2659	.2670	.2690	.2570	.2533
1 if Age 45-54	.3235	.2496	.2449	.2293	.2090	.2020	.1919
1 if Age 55-64	.2069	.1438	.1443	.1359	.1206	.1151	.1103
1 if Age 65-99	.0605	.0432	.0456	.0391	.0354	.0380	.0400
1 if Foreign Born	.8256	.6742	.6658	.6890	.6207	.4808	.4227
1 if Nonwhite	.6018	.5299	.5269	.5370	.4988	.4450	.4202
1 if Hispanic	.1365	.1661	.1615	.1592	.1545	.1852	.2121
1 if Education 10	.2030	.2045	.1973	.1903	.1757	.1743	.1780
1 if Education 12	.2231	.2484	.2498	.2414	.2326	.2392	.2474
1 if Education 14	.2425	.2747	.2759	.2748	.2841	.2952	.2995
1 if Education 16	.2278	.2329	.2430	.2655	.2897	.2800	.2665
1 if Education Missing	.1036	.0394	.0340	.0280	.0179	.0113	.0086
Receipts 4853	40,180	23,540	22,950	21,340	16,160	11,450	10,460
Expenses 4853	27,890	16,350	16,250	15,090	11,780	8,860	8,360
Net Receipts 4853	12,290	7,190	6,690	6,250	4,380	2,590	2,110
1 if W&S Earnings	.1619	.4358	.4661	.5205	.6437	.7264	.7500
Sample Size (Thousands)	119	50	49	58	110	246	368

Source: Estimates from authors' calculations based on data infrastructure described in text.

Appendix Table B-2B: Descriptive Statistics (Means), Nonemployer Sole Proprietors Not in NAICS 4853: Taxi and Limousine Services, 2011 Incumbents and 2011-2016 Entrants

	Incumbent	Entrants					
	2011	2011	2012	2013	2014	2015	2016
1 if Female	.4388	.4685	.4704	.4717	.4696	.4741	.4748
1 if Age 14-20	.0059	.0371	.0359	.0370	.0363	.0363	.0357
1 if Age 21-24	.0263	.0829	.0825	.0861	.0846	.0844	.0825
1 if Age 25-34	.1533	.2470	.2461	.2529	.2521	.2572	.2609
1 if Age 35-44	.2184	.2259	.2239	.2214	.2186	.2193	.2198
1 if Age 45-54	.2538	.2044	.2015	.1959	.1939	.1915	.1876
1 if Age 55-64	.2159	.1381	.1404	.1371	.1416	.1385	.1382
1 if Age 65-99	.1265	.0647	.0696	.0695	.0730	.0728	.0754
1 if Foreign Born	.1949	.2007	.2032	.2079	.2039	.2057	.2086
1 if Nonwhite	.1738	.2500	.2456	.2477	.2420	.2448	.2422
1 if Hispanic	.1236	.1568	.1577	.1650	.1623	.1659	.1689
1 if Education 10	.1372	.1617	.1599	.1638	.1597	.1598	.1584
1 if Education 12	.2383	.2533	.2522	.2526	.2502	.2495	.2477
1 if Education 14	.2737	.2903	.2909	.2910	.2917	.2926	.2935
1 if Education 16	.2841	.2698	.2727	.2697	.2750	.2754	.2809
1 if Education Missing	.0668	.0249	.0242	.0229	.0234	.0227	.0195
Receipts	38,380	19,250	19,420	18,440	19,830	19,020	18,480
Expenses	17,200	9,140	9,230	8,960	9,560	9,330	9,090
Net Receipts	21,180	10,110	10,190	9,480	10,270	9,680	9,390
1 if W&S Earnings	.4237	.6165	.6283	.6405	.6509	.6718	.6801
Sample Size (Thousands)	12,620	5,661	5,575	5,664	5,973	5,820	5,866

Source: Estimates from authors' calculations based on data infrastructure described in text.

Appendix Table B-3: Uber's Presence in a Market and Nonemployer Entry into NAICS 4853, Taxi and Limousine Services, 2011-2016, Quadratic Specification and Comparison of Linear and Quadratic Four-Year Effects

A. Estimated Model Coefficients from the Quadratic Specification

			(1)		(2)	
	Mean	[S.D.]	Coef.	(SE)	Coef.	(SE)
Year	2014	[1.70]	-0.0010	(0.0030)	0.0027	(0.0020)
YearsUber	1.14	[1.57]	0.0078	(0.0077)	-0.0128	(0.0069)
YearsUberSquared	3.77	[7.10	0.0061	(0.0021)	0.0125	(0.0017)
Years Uber * Regulation	0.79	[1.49]			0.0106	(0.0102)
Years Uber Squared* Regulation	2.84	[6.80]			-0.0035	(0.0024)
Years Uber * Regulation * NY CBSA	0.22	[0.96]			-0.0429	(0.0080)
Years UberSquared * Regulation * NY CBSA	0.96	[4.80]			0.0011	(0.0015)
R-squared			0.0015		0.0016	

B. Comparison of Effects on Entry to NAICS 4853 Four Years After Uber Entry, Linear versus Quadratic Specification

	Linear Model		Quadratic Model	
	Estimate	(SE)	Estimate	(SE)
Col. (1): No interactions				
YearsUber	0.1616	(0.0148)	0.1370	(0.0152)
Col. (2): Interactions with Regulation and NY CBSA				
YearsUber	0.1512	(0.0200)	0.1625	(0.0132)
YearsUber + YearsUber*Reg	0.1827	(0.0152)	0.1507	(0.0142)
YearsUber + YearsUber*Reg + YearsUber*NY	0.1225	(0.0053)	-0.0149	(0.0048)

Note: Sample is person-year observations for individuals age 14 to 99 at risk for entry as a nonemployer sole proprietor to NAICS 4853, Taxi and Limousine Services, in a given year. Dependent variable=100 if person enters NAICS 4853 in observation year, else=0; mean=0.0582. YearsUber is number of years Uber has been present in a Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0; mean of Regulation=0.3884 and mean of Regulation*NY CBSA=0.0637. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; 919 CBSA dummies; and CBSA missing indicator. Standard errors clustered at CBSA level. N=1,514,000,000.

Appendix Table B-4: Uber's Presence in a Market and Exit of Incumbents in NAICS 4853, Taxi and Limousine Services, from Any Employment, 2010-2015

	All 2010 incumbents (1)		Incumbents with <$12,000 NAICS 4853 net earnings in 2010 (2)		Incumbents with ≥$12,000 NAICS 4853 net earnings in 2010 (3)	
	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)
Year	2013	-0.0136	2013	-0.0202	2013	0.0043
		(0.0018)		(0.0027)		(0.0024)
YearsUber	2.17	0.0092	1.92	0.0127	2.42	-0.0041
	[1.87]	(0.0021)	[1.83]	(0.0032)	[1.89]	(0.0024)
YearsUber * Regulation	1.85	-0.0018	1.56	-0.0040	2.15	0.0006
	[1.95]	(0.0014)	[1.86]	(0.0023)	[1.99]	(0.0014)
YearsUber * Regulation * NY CBSA	1.27	-0.0026	0.97	-0.0067	1.59	-0.0013
	[1.90]	(0.0010)	[1.72]	(0.0014)	[2.02]	(0.0013)
R-squared		0.0286		0.0329		0.0214
Dependent variable mean		0.1078		0.1347		0.0769
N		510,000		263,000		247,000

Note: Sample is person-year observations for individuals who were NAICS 4853 nonemployer sole proprietors in both 2009 and 2010 and remained a nonemployer sole proprietor or had wage and salary earnings through the observation year. Dependent variable=1 if not a nonemployer and had no wage and salary earnings in following year, implying observation year exit, else=0. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; CBSA dummies (778 in model 1, 504 in model 2 and 743 in model 3); and CBSA missing indicator. Standard errors clustered at CBSA level.

Appendix Table B-5: Uber's Presence in a Market and Changes in Net Earnings from All Sources of Incumbents in NAICS 4853, Taxi and Limousine Services, 2011-2015

	Net Earnings in t - Net Earnngs in 2010						(Net Earnings in t - Net Earnings in 2010)/ Net Earnings in 2010	
	All 2010 incumbents (1)		Incumbents with 2010 NAICS 4853 net earnings <$12,000 (2)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (3)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (4)	
	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)
Year	2013	204	2013	465	2013	-131	2013	0.0033
		(86)		(98)		(121)		(0.0059)
YearsUber	1.83	-219	1.63	-128	2.04	-318	2.04	-0.0193
	[1.60]	(89)	[1.56]	(86)	[1.62]	(160)	[1.62]	0.0080
YearsUber * Regulation	1.59	153	1.35	153	1.83	256	1.83	0.0166
	[1.66]	(130)	[1.60]	(93)	[1.69]	(189)	[1.69]	(0.0090)
YearsUber * Regulation * NY CBSA	1.12	75	0.86	219	1.39	174	1.39	0.0062
	[1.64]	(115)	[1.50]	(80)	[1.73]	(147)	[1.73]	(0.0070)
R-squared		0.015		0.0265		0.0262		0.0192
Dependent variable mean		$487		$2,509		-$1,569		-0.0300
N		396,000		200,000		197,000		197,000

Note: Sample is person-year observations for individuals who were NAICS 4853 nonemployer sole proprietors in both 2009 and 2010 and remained a nonemployer sole proprietor or had wage and salary income through observation year. Dependent variables defined based on net earnings in 2015 dollars. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; CBSA dummies (734 in model 1, 691 in model 2 and 474 in models 3 and 4); CBSA missing indicator; and an exit dummy =1 if person exited employment during year, else=0. Standard errors clustered at CBSA level.

Appendix Table B-6: Uber's Presence in a Market and Incumbent Exit from NAICS 4853, Taxi and Limousine Services, 2010-2015, Quadratic Specification and Comparison of Linear and Quadratic Four-Year Effects

	All 2010 incumbents (1)		Incumbents with <$12,000 NAICS 4853 net earnings in 2010 (2)		Incumbents with ≥$12,000 NAICS 4853 net earnings in 2010 (3)	
	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)
Year	2013	-0.0172	2013	-0.0236	2013	0.0011
		(0.0020)		(0.0030)		(0.0020)
YearsUber	2.13	-0.0006	1.88	-0.0035	2.39	-0.0059
	[1.87]	(0.0050)	[1.81]	(0.0060)	[1.89]	(0.0050)
YearsUberSquared	8.03	0.0027	6.84	0.0041	9.28	0.0008
	[10.21]	(0.0010)	[9.48]	(0.0010)	[10.79]	(0.0010)
YearsUber * Regulation	1.82	-0.0073	1.53	-0.0067	2.12	-0.0080
	[1.93]	(0.0050)	[1.84]	(0.0060)	[1.98]	(0.0040)
YearsUberSquared*Regulation	7.03	0.0007	5.72	0.0000	8.41	0.0015
	[10.22]	(0.0010)	[9.35]	(0.0010)	[10.89]	(0.0010)
YearsUber * Regulation * NY CBSA	1.26	-0.0059	0.95	-0.0259	1.58	0.0085
	[1.88]	(0.0030)	[1.69]	(0.0040)	[2.01]	(0.0030)
YearsUberSquared*Regulation* NY CBSA	5.11	-0.0006	3.77	0.0014	6.52	-0.0022
	[9.71]	(0.0000)	[8.52]	(0.0010)	[10.64]	(0.0000)
R-squared		0.0353		0.0416		0.0258
Dependent variable mean		0.1269		0.1566		0.0933
N		484,000		248,000		236,000

B. Comparison of Effects on Exit from NAICS 4853 Four Years After Uber Entry, Linear versus Quadratic Specifications

	Linear Model		Quadratic Model	
	Estimate	(SE)	Estimate	(SE)
Col. (1): All 2010 incumbents				
YearsUber	0.0524	(0.0104)	0.0407	(0.0093)
YearsUber + YearsUber*Reg	0.0403	(0.0098)	0.0228	(0.0093)
YearsUber + YearsUber*Reg + YearsUber*NYC	0.0284	(0.0082)	-0.0112	(0.0076)
Col. (2):Incumbents <$12,000 2010 NAICS 4853 net earnings				
YearsUber	0.0664	(0.0144)	0.0512	(0.0115)
YearsUber + YearsUber*Reg	0.0444	(0.0123)	0.0243	(0.0119)
YearsUber + YearsUber*Reg + YearsUber*NYC	0.0138	(0.0097)	-0.0565	(0.0095)
Col. (3): Incumbents ≥$12,000 2010 NAICS 4853 net earnings				
YearsUber	-0.0032	(0.0100)	-0.0100	(0.0111)
YearsUber + YearsUber*Reg	-0.0046	(0.0109)	-0.0172	(0.0115)
YearsUber + YearsUber*Reg + YearsUber*NYC	-0.0117	(0.0088)	-0.0188	(0.0089)

Note: Sample is person-year observations for individuals who were NAICS 4853 nonemployer sole proprietors in both 2009 and 2010 and remained a NAICS 4853 nonemployer sole proprietor through observation year. Dependent variable=1 if not a NAICS 4853 nonemployer in following year, implying observation year exit, else=0. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; CBSA dummies (778 in model 1, 504 in model 2 and 743 in model 3); and CBSA missing indicator. Standard errors clustered at CBSA level.

Appendix Table B-7: Uber's Presence in a Market and Changes in Incumbents' Net Earnings in NAICS 4853, Taxi and Limousine Services, 2011-2015, Quadratic Specification and Comparison of Linear and Quadratic Four-Year Effects

A. Estimated Model Coefficients from Quadratic SpecificationS

	Net Earnings in t - Net Earnngs in 2010						(Net Earnings in t - Net Earnings in 2010)/ Net Earnings in 2010	
	All 2010 incumbents (1)		Incumbents with 2010 NAICS 4853 net earnings <$12,000 (2)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (3)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (4)	
	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)
Year	2013	-20.16	2013	415.70	2013	-519.00	2013	-0.0194
		(47.41)		(47.91)		(63.71)		(0.0030)
YearsUber	1.82	40.59	1.62	70.45	2.03	-3.64	2.03	-0.0011
	[1.60]	(117.10)	[1.56]	(120.10)	[1.61]	(206.80)	[1.61]	(0.0120)
YearsUberSquared	5.88	-63.33	5.04	-55.41	6.72	-73.69	6.72	-0.0039
	[7.39]	(27.85)	[6.89]	(28.93)	[7.76]	(48.20)	[7.76]	(0.0030)
YearsUber * Regulation	1.58	322.60	1.33	314.60	1.82	350.30	1.82	0.0173
	[1.66]	(159.60)	[1.59]	(159.80)	[1.69]	(244.40)	[1.69]	(0.0130)
YearsUberSquared*Regulation	5.23	-52.65	4.29	-39.74	6.17	-42.25	6.17	-0.0010
	[7.43]	(48.35)	[6.85[	(42.13)	[7.86]	(69.08)	[7.86]	(0.0030)
YearsUber * Regulation * NY CBSA	1.12	383.20	0.85	191.10	1.39	799.90	1.39	0.0379
	[1.63]	(146.30)	[1.48]	(139.20)	[1.72]	(166.10)	[1.72]	(0.0080)
YearsUberSquared*Regulation* NY CBSA	3.92	4.05	2.93	42.05	4.90	-31.56	4.90	-0.0017
	[7.16]	(42.88)	[6.36]	(33.22)	[7.75]	(52.01)	[7.75]	(0.0020)
R-Squared		0.017		0.0331		0.0338		0.0389
Dependent variable mean		-$203		$1,998		-$2,393		-0.0800
N		371,000		185,000		186,000		186,000

B. Comparison of Effects on Net Earnings in NAICS 4853 Four Years After Uber Entry, Linear versus Quadratic Specifications

	Linear Model		Quadratic Model	
	Estimate	(SE)	Estimate	(SE)
Col. (1): All 2010 incumbents				
YearsUber	-$888	($262.40)	-$851	($187.00)
YearsUber + YearsUber*Reg	-$378	($394.50)	-$403	($328.10)
YearsUber + YearsUber*Reg + YearsUber*NYC	$177	($188.80)	$1,194	($177.60)
Col. (2):Incumbents <$12,000 2010 NAICS 4853 net earnings				
YearsUber	-$636	($212.80)	-$605	($179.40)
YearsUber + YearsUber*Reg	$6	($302.50)	$18	($284.20)
YearsUber + YearsUber*Reg + YearsUber*NYC	$915	($175.00)	$1,455	($176.60)
Col. (3): Incumbents ≥$12,000 2010 NAICS 4853 net earnings				
YearsUber	-$1,195	($413.60)	-$1,194	($255.60)
YearsUber + YearsUber*Reg	-$412	($576.10)	-$468	($479.70)
YearsUber + YearsUber*Reg + YearsUber*NYC	$919	($264.40)	$2,227	($242.90)
Col. (4): Incumbents ≥$12,000 2010 NAICS 4853 net earnings				
YearsUber	-0.0664	(0.0216)	-0.0676	(0.0137)
YearsUber + YearsUber*Reg	-0.0122	(0.0241)	-0.0139	(0.0213)
YearsUber + YearsUber*Reg + YearsUber*NYC	0.0530	(0.0122)	0.1115	(0.0122)

Note: Sample is person-year observations for individuals who were NAICS 4853 nonemployer sole proprietors in both 2009 and 2010 and remained a NAICS 4853 nonemployer sole proprietor through observation year. Dependent variables defined based on net earnings in 2015 dollars. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; CBSA dummies (713 in model 1, 674 in model 2 and 457 in models 3 and 4); CBSA missing indicator; and an exit dummy =1 if person exited NAICS 4853 during year, else=0. Standard errors clustered at CBSA level.

Appendix C: Using Expenses to Proxy Miles Driven

Our estimate of driver miles is calculated as total expenses reported by the driver on Schedule C divided by the Internal Revenue Service (IRS) mileage rate. While simple to implement, this measure has some significant limitations as a proxy for miles driven. First, this measure is only directly applicable to drivers who own or lease their vehicle and use the standard mileage expense deduction to determine their vehicle expenses. Using the mileage deduction is an alternative to claiming actual vehicle expenses, such as depreciation, lease payments, maintenance and repairs, gasoline, oil, insurance and vehicle registration fees. Both owners and lessees may claim the mileage deduction, though they are not permitted to switch back and forth between the two methods of determining their expense deductions (Internal Revenue Service 2016). We do not have any way to know how individual drivers calculated their reported expenses. Using our proxy implicitly assumes that, for drivers who use actual vehicle expenses, those expenses are similar to what a calculation using the IRS mileage rate would produce. Second, deductible expenses also include other fees paid to the taxi or ridesharing company together with expenses such as parking fees or tolls. So long as these other expenses are relatively fixed over time, the change in reported expenses may still allow us to construct a reasonable proxy for the change in miles driven. To the extent that incumbent drivers who continue in the taxi and limousine industry shift from traditional taxi companies to ride sharing companies, however, they will face a different fee structure and the fees they pay may change. All of this implies that our estimate of changes in mileage based on changes in reported expenses should be interpreted with considerable caution.

With this caveat in mind, we have estimated models for the change in incumbent driver miles like those reported in Table 4 and Table B-7 for the change in incumbent driver net earnings. These results are reported in Table C-1 (linear specifications) and C-2 (quadratic specifications). Similar to the results for net earnings, the dependent variable in these models is either the absolute change or the percentage change in estimated miles driven. The samples in columns (1) through (3) of these tables are the same as in the corresponding Table 4 columns; the sample in column (4) excludes the small percentage of drivers with net earnings of $12,000 or more who reported zero expenses.

In the linear models reported in Table C-1, the estimates imply that the miles driven by incumbent drivers increased following Uber entry into a CBSA, especially for low-earning drivers. Taking the estimates at face value, in the fourth year after Uber entered a CBSA, annual miles driven by incumbent drivers in unregulated areas rose by about 4,200 miles; the implied increase for drivers who earned less than $12,000 in 2010 was larger (about 4,900 miles) and the implied increase for drivers earnings $12,000 or more in 2010 was smaller (about 3,200 miles). These estimates translate into increases of 81, 94 and 62 miles per week, respectively. Being in a regulated CBSA other than New York had no statistically significant effect on the estimates, but the estimated change in miles driven was notably smaller for incumbent drivers in the New York CBSA. The estimated effects of Uber entry on miles driven four years later based on the quadratic model are similar.

Likely reflecting the fact that our mileage estimate is based on a noisy calculation, the estimated coefficients reported in Tables C-1 and C-2 are estimated less precisely than the corresponding coefficients in the net earnings models. For example, for a high-earning driver living in a non-regulated city where Uber had entered four years earlier, for example, the estimated coefficients from Table 4 imply that Uber entry caused real earnings to be almost 7% lower relative to the driver's 2010 earnings than they otherwise would have been. This estimate is statistically significant at the 1% level. In the corresponding model for estimated mileage reported in Table C-1, the point estimate of the coefficient implies that, four years after Uber entry, mileage is about 6% higher relative to the driver's 2010 approximate mileage than it otherwise would have been, but this estimate is statistically insignificant.

Reference

Internal Revenue Service. 2016. *2016 Instructions for Schedule C: Profit or Loss from Business.* Accessed on November 2, 2025 at https://www.irs.gov/pub/irs-prior/i1040sc--2016.pdf .

Table C-1: Uber's Presence in a Market and Changes in Approximate Miles Driven by Incumbents in NAICS 4853, Taxi and Limousine Services, 2011-2015

	Miles Driven in t - Miles Driven in 2010						(Miles Driven in t - Miles Driven in 2010)/ Miles Driven in 2010
	All 2010 incumbents (1)		Incumbents with 2010 NAICS 4853 net earnings <$12,000 (2)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (3)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (4)
	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Coef. (SE)
Year	2013	93.4	2013.0	106.6	2013.0	81.5	0.056
		(199.8)		(241.9)		(276.7)	(0.025)
YearsUber	1.82	1044.0	1.6	1220.0	2.0	811.7	0.016
	[1.60]	(294.3)	[1.56]	(282.7)	[1.61]	(401.7)	(0.023)
YearsUber * Regulation	1.58	66.4	1.3	349.0	1.8	-180.2	-0.002
	[1.66]	(340.7)	[1.59]	(329.3)	[1.69]	(411.2)	(0.023)
YearsUber * Regulation * NY CBSA	1.12	-884.6	0.9	-404.7	1.4	-921.0	-0.038
	[1.63]	(293.2)	[1.48]	(268.3)	[1.72]	(363.5)	(0.022)
R-squared		0.0268		0.0422		0.0250	0.0137
Dependent variable mean		5,111		6,056		4,170	0.3493
N		371,000		185,000		186,000	176,000

Note: Sample is person-year observations for individuals who were NAICS 4853 nonemployer sole proprietors in both 2009 and 2010 and remained a NAICS 4853 nonemployer sole proprietor through observation year. Dependent variables defined based on net earnings in 2015 dollars. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; CBSA dummies (713 in model 1, 674 in model 2 and 457 in models 3 and 4); CBSA missing indicator; and an exit dummy =1 if person exited NAICS 4853 during year, else=0. Column (4) explanatory variable means [standard deviations] not reported due to secondary disclosure issues. Standard errors clustered at CBSA level.

Appendix Table C-2: Uber's Presence in a Market and Changes in Approximate Miles Driven by Incumbents in NAICS 4853, Taxi and Limousine Services, 2011-2015, Quadratic Specification and Comparison of Linear and Quadratic Four-Year Effects

A. Estimated Model Coefficients from Quadratic Specification

	All 2010 incumbents (1)		Incumbents with 2010 NAICS 4853 net earnings <$12,000 (2)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (3)		Incumbents with 2010 NAICS 4853 net earnings ≥$12,000 (4)
	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Mean [SD]	Coef. (SE)	Coef. (SE)
Year	2013	-131.4	2013	-0.6	2013	-258.9	0.0475
		(253.6)		(264.6)		(315.4)	(0.0250)
YearsUber	1.82	68.3	1.62	324.1	2.03	-312.6	-0.0043
	[1.60]	(559.2)	[1.56]	(648.1)	[1.61]	(805.8)	(0.0330)
YearsUberSquared	5.88	271.6	5.04	255.3	6.72	298.5	0.0050
	[7.39]	(122.8)	[6.89]	(150.9)	[7.76]	(150.2)	(0.0070)
YearsUber * Regulation	1.58	1430.0	1.33	1662.0	1.82	1195.0	0.0161
	[1.66]	(736.9)	[1.59]	(868.8)	[1.69]	(845.1)	(0.0440)
YearsUberSquared*Regulation	5.23	-426.6	4.29	-397.0	6.17	-444.6	-0.0066
	[7.43[	(194.1)	[6.85[	(222.9)	[7.86]	(215.1)	(0.0130)
YearsUber * Regulation * NY CBSA	1.12	1721.0	0.85	756.7	1.39	2725.0	0.0714
	[1.63]	(619.5)	[1.48]	(646.1)	[1.72]	(707.9)	(0.0320)
YearsUberSquared*Regulation* NY CBS	3.92	-362.1	2.93	-134.1	4.90	-526.5	-0.0169
	[7.16]	(100.4)	[6.36]	(129.9)	[7.75]	(91.2)	(0.0090)
R-Squared		0.027		0.0386		0.0254	0.0137
Dependent variable mean		5,111		6,056		4,170	0.3493
N		371,000		185,000		186,000	176,000

B. Comparison of Effects on Miles Driven by NAICS 4853 Incumbents Four Years After Uber Entry, Linear versus Quadratic SpecificationS

	Linear Model		Quadratic Model	
	Estimate	(SE)	Estimate	(SE)
Col. (1): All 2010 incumbents				
YearsUber	4,176	(1176)	4,619	(1203)
YearsUber + YearsUber*Reg	4,440	(1544)	3,514	(1645)
YearsUber + YearsUber*Reg + YearsUber*NYC	901	(863)	4,605	(833)
Col. (2):Incumbents <$12,000 2010 NAICS 4853 net earnings				
YearsUber	4,880	(1608)	5,382	(1074)
YearsUber + YearsUber*Reg	6,278	(1467)	5,676	(1532)
YearsUber + YearsUber*Reg + YearsUber*NYC	4,659	(911)	6,557	(899)
Col. (3): Incumbents ≥$12,000 2010 NAICS 4853 net earnings				
YearsUber	3,248	(1132)	3,526	(1697)
YearsUber + YearsUber*Reg	2,526	(2035)	1,192	(2180)
YearsUber + YearsUber*Reg + YearsUber*NYC	-1,158	(1196)	3,666	(1097)
Col. (4): Incumbents ≥$12,000 2010 NAICS 4853 net earnings				
YearsUber	0.0640	(0.0920)	0.0632	(0.0886)
YearsUber + YearsUber*Reg	0.0564	(0.1241)	0.0219	(0.1194)
YearsUber + YearsUber*Reg + YearsUber*NYC	-0.0968	(0.0849)	0.0362	(0.0907)

Note: Sample is person-year observations for individuals who were NAICS 4853 nonemployer sole proprietors in both 2009 and 2010 and remained a NAICS 4853 nonemployer sole proprietor through observation year. Dependent variables defined based on net earnings in 2015 dollars. YearsUber is number of years Uber has been present in Core Based Statistical Area (CBSA); =0 if observation outside a CBSA or Uber not entered by given year. Regulation=1 if regulations in CBSA's core city limit taxi numbers, else=0. All regressions include controls for gender, age, foreign born, nonwhite, Hispanic, and education; indicator for missing education; percent employment growth in CBSA from year t-5 through year t-1; CBSA dummies (713 in model 1, 674 in model 2 and 457 in models 3 and 4); CBSA missing indicator; and an exit dummy =1 if person exited NAICS 4853 during year, else=0. Column (4) explanatory variable means [standard deviations] not reported due to secondary disclosure issues. Standard errors clustered at CBSA level.