# **Driving the Gig Economy**\*

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#### **Abstract**

There is much to be learned about gig workers and how gig work fits into their careers. In this paper, we focus on Taxi and Limousine Services, the sector in which the prototypical gig worker—a contract driver for a ridesharing company—reports self-employment activity. Using administrative data for people with self-employment activity in this sector together with administrative data on the same individuals' wage and salary activity, we explore who these gig workers are and how they use gig work. For comparison, we similarly explore the dynamics of entry into and exit from self-employment among the universe of U.S. nonemployer sole proprietors. Growth in the number of nonemployers in Taxi and Limousine Services has dramatically outpaced the growth in any other industry. Nonemployer entrants to Taxi and Limousine Services are very different from incumbents in the industry as well as from both entrants and incumbents in other industries, not only in their characteristics but also in the way they combine self-employment with wage and salary work. We examine push and pull factors that contribute to workers entering self-employment in Taxi and Limousine Services and find evidence consistent with lowered barriers to entry having made ride-sharing work a more attractive option for people who experience adverse economic shocks.

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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 been focused on the increase in jobs mediated through various online platforms. Terms like the "sharing" and "on demand" economy also have been used to refer to this sort of work activity, highlighting the opportunities that apps on smartphones and other webbased applications create for buyers to acquire goods and services directly from providers. There is a widespread perception that new technology is producing an accelerated pace of change in the organization of work that is having important effects on both workers and firms.

Quantifying the growth of the gig economy has proved challenging. Individuals engaged in gig work should be recorded as self-employed in standard household surveys such as the Current Population Survey (CPS) and American Community Survey. These household surveys, however, show little or no growth in self-employment in the post-2000 period, either with respect to individuals' main jobs or with respect to having any self-employment income over the course of a year. In contrast, administrative data show substantial increases in self-employment activity over this same period (Katz and Krueger 2016, Abraham et al. 2017). The discrepancy in the patterns in household survey data as compared to administrative data is an area of active research, but it raises questions about the use of standard household surveys to track the gig economy. In this paper, we use administrative data from the Census Bureau's Nonemployer Statistics program to study the growth of the gig economy and learn about what is driving that growth.

More specifically, we focus on the growth of self-employment activity in the Taxi and Limousine Services industry (NAICS 4853). This is the industry where individuals who are contracting as drivers for taxi, limousine and ridesharing companies should be expected to report their self-employment earnings. It has been especially affected by the development of new

technology that makes it easy for producers (drivers) and customers (riders) to connect with one another, thereby significantly lowering the barriers to participation for prospective entrants.

Because these developments have played such a central role in the industry, studying Taxi and Limousine Services offers a unique opportunity to learn about the effects of this sort of new technology.

Published Census Bureau nonemployer statistics confirm that there has been dramatic growth in self-employment activity in the Taxi and Limousine Services industry in the post-2010 period. The number of people with self-employment earnings in the industry grew especially rapidly after 2013, increasing from about 224 thousand in 2013 to about 700 thousand in 2016, with 85 percent of that increase occurring between 2014 and 2016. Although self-employment activity more generally also grew over the same period, from about 23.0 million nonemployer businesses in 2013 to about 24.8 million nonemployer businesses in 2016, the dramatic growth in the Taxi and Limousine Services industry has far outpaced that in any other industry. One goal of our analysis is to compare and contrast the patterns of growth in self-employment activity in the Taxi and Limousine Services industry with the more general rise in self-employment activity.

Our analysis rests on comprehensive records that allow us to observe both self-employment and wage and salary activity for essentially the entire working population. We integrate longitudinal person-level information on the universe of U.S. sole proprietors with longitudinal information on wage and salary activity for these same individuals. These matched administrative data are further enhanced with information about worker characteristics including gender, age, race, ethnicity, foreign born status, and education. Since the data are linked longitudinally, we can track

<sup>&</sup>lt;sup>1</sup> Our data cover about 98 percent of private wage and salary employment plus state and local government, and all reported self-employment among sole proprietors without employees that generates \$1,000 or more in gross receipts during a year.

entry into and exit from self-employment activity as well as entry into and exit from wage and salary activity and the changes in earnings associated with these transitions. Approximately 20 million individuals have self-employment activity in each of the years for which we have micro data, which at this time includes 2010 and 2012 through 2015.<sup>2</sup>

We begin with a descriptive analysis of self-employment in the Taxi and Limousine Services industry, which as already noted is the industry that has experienced far and away the most rapid growth in self-employment activity over our sample period. Self-employment in this industry is inclusive of traditional taxi and limousine service drivers as well as those whose driving activity is mediated by an online platform ridesharing app.<sup>3</sup> In this respect, it is useful to note that most traditional taxi and limousine service drivers are self-employed independent contractors.<sup>4</sup>

Over the period we study, new entrants to NAICS 4853 look increasingly different from incumbent taxi and limousine drivers. Compared to incumbents, entrants during the period of rapid growth in this industry have been much more likely to be female, young, U.S. born and white. In each new cohort, entrants also have been more likely than either incumbents or those in the previous cohort of entrants to have wage and salary income in addition to self-employment income from driving in their year of entry. On average, for entrants who had both prior year and current year wage and salary income, entry was accompanied by a modest decline in wage and salary earnings that was partially mitigated by earnings from driving; in 2015, for example, this group experienced a decline of \$2,563 in wage and salary income and the addition of \$1,246 in net

<sup>&</sup>lt;sup>2</sup> For the next iteration of the paper, we will have annual micro data covering the period from 2010 through 2016.

<sup>&</sup>lt;sup>3</sup> The nonemployer data do not include information on the taxi or ridesharing companies with whom drivers contract. As will become clear, however, there are dramatic differences between incumbents and entrants in NAICS 4853 that are closely linked to when online platform ridesharing becomes available in a geographic area.

<sup>&</sup>lt;sup>4</sup> Occupational Employment Statistics data from the Bureau of Labor Statistics show that in 2010 there were about 42 thousand wage and salary drivers in the Taxi and Limousine Services industry. The published nonemployer data show about 160 thousand sole proprietors in this industry in 2010.

nonemployer income from driving.<sup>5</sup> For those who fully transitioned from wage and salary activity in the prior year to self-employment in their entry year, a larger loss in wage and salary earnings also was partially offset by an increase in nonemployer income; in 2015, for example, those in this group lost \$14,030 in wage and salary income and gained \$6,031 in net nonemployer income from driving. Entrants to NAICS 4853 who had no wage and salary income either in the prior year or the year of entry had relatively modest net nonemployer earnings; in 2015, their average net receipts of \$5,667 from driving were less than a third as large as the average of \$18,390 in net receipts for those with no prior year or current year wage and salary earnings who entered self-employment in other industries. All of these patterns are robust to controlling for changes in the characteristics of entrants to self-employment over time. We interpret what we are seeing as suggestive that many entrants into the rideshare industry are using that work to smooth fluctuations in other earned income or perhaps to supplement some other source of support, rather than relying entirely or even primarily on income from ridesharing.

The characteristics of entrants stand in sharp contrast to those for incumbents in the Taxi and Limousine Services industry. Nonemployers incumbent in the industry in 2013 were more likely to be male, older, foreign born, and nonwhite. Incumbents also were much less likely to have wage and salary activity concurrently with (i.e., in the same year as) self-employment activity.

The patterns for entrants and incumbents in NAICS 4853 also differ substantially from the patterns for their counterparts in other industries over this period. The growth in self-employment in other industries has been considerably less rapid than the growth in the ridesharing industry.

Except with respect to their age distribution (entrants tend to be younger than incumbents), entrants

<sup>&</sup>lt;sup>5</sup> In most of what follows, we use net receipts, defined as gross receipts minus claimed expenses, as the measure of earnings from self-employment. We also report some information on gross receipts, which can be interpreted as an upper bound on self-employment earnings.

and incumbents in other industries differ relatively little in their characteristics. Entrants in other industries are somewhat more likely than incumbents to have wage and salary income in the year of entry, but the incumbent-entrant differential is substantially smaller than in NAICS 4853. While some of the growth in other industries may be attributable to the development of new technologies for matching workers with potential customers and clients, the slower pace of growth in self-employment outside of NAICS 4853 and the fact that entrants and incumbents in other industries look so much more similar to each other suggests that any growth in gig-like activities elsewhere in the economy has had much less of an impact to date on the structure of work.

We build on our descriptive analysis to investigate some of the factors that have contributed to the surge of entry into self-employment in NAICS 4853. We hypothesize that, by lowering the barriers to entry, the entrance of online platform ridesharing companies should pull workers into the Taxi and Limousine Services industry. Variation in whether and when online platform ridesharing has become available in different metropolitan areas allows us to identify the effects of that potentially important pull factor. We find that the pace of entry into nonemployer activity in NAICS 4853 rises with the number of years that online platform ridesharing has been available in a metropolitan area, especially for those with wage and salary earnings in the prior year.

We use an indicator for whether a worker has experienced a mass layoff in the prior year as a plausibly exogenous push factor. For metropolitan areas in which online platform ridesharing activity is not available, displacement in the prior year yields a proportionally greater increase in the rate of entry into other non-employer industries than into the Taxi and Limousine Services industry. For metropolitan areas in which online platform ridesharing activity has become available, however, displacement increases the probability of entry (relative to the mean entry rate) into nonemployer activity in NAICS 4853 by much more than the probability of entry into other nonemployer industries. This gap grows with the number of years online platform ridesharing has

been available in a metropolitan area. Similar to the pattern of diffusion for other technological innovations, it appears to take time for the full effects of the introduction of ridesharing technology to be realized.

The paper proceeds as follows. Section II provides background in the form of a review of some of the previous literature relevant to our project. Section III describes the data used in our analysis and Section IV presents a set of descriptive findings. In Section V, we consider the factors that lead to entry into self-employment into NAICS 4853. Section VI offers some concluding remarks.

## II. Background

Self-employment historically has offered an alternative to wage and salary employment that attracts a segment of the workforce. Various explanations have been offered for the decision to enter self-employment. A number of studies have pointed to the role that having a self-employed parent or other exposure to self-employment early in life may play in an individual's decision to enter self-employment (see, for example, Taylor 1996, Blanchflower and Oswald 2007, or Fairlie and Robb 2007). For some who choose self-employment, the attraction of being one's own boss appears to be a key factor. Hamilton (2000), for example, finds that entrepreneurs often persist in self-employment even though they have lower initial earnings and slower earnings growth than would have been predicted had they chosen wage employment. He argues that these findings imply the existence of substantial nonpecuniary benefits to being self-employed. Hurst and Pugsley (2011) cite survey evidence on the reasons entrepreneurs give for forming a business. More than half of respondents to the survey cited nonpecuniary considerations such as "wanting flexibility over schedule" or "to be one's own boss" as the primary reason for starting their own businesses.

Other studies have argued that many people choose self-employment primarily because they face poor opportunities in the wage and salary market. In analyses using data from the National Longitudinal Survey of Youth 1979, Rissman (2003, 2006) inds that individuals living in areas where the local labor market is weak are more likely to enter self-employment and that entry to self-employment exhibits a cyclical pattern, with people being more likely to enter self-employment when aggregate economic conditions are weak and to exit when aggregate economic conditions are strong. In contrast, other studies (e.g., Blanchflower 2000) have found a negative relationship between the self-employment rate and the unemployment rate. Using information from the original National Longitudinal Surveys on individuals' own circumstances, Evans and Leighton (1989) find that, among white men, those who were unemployed, earned low wages or changed jobs frequently were more likely to become self-employed. In a study that uses data from the Working and Living Conditions Survey for Spain and the Displaced Worker Supplement to the CPS for the United States, Alba-Ramirez (1994) finds that displaced workers who had been unemployed for a longer period of time were more likely to enter self-employment.

Although much of the interest in self-employment stems from the desire to understand how small businesses contribute to economic growth, many small businesses never grow larger and many small business owners say that they are not interested in expanding or hiring employees (Hurst and Pugsley 2011). There has been growing recognition of the considerable heterogeneity among the self-employed (see, for example, Davis et al 2009, Hurst and Pugsley 2011 or Levine and Rubinstein 2017). Levine and Rubinstein (2017) suggest that making a distinction between the owners of incorporated and unincorporated businesses is a convenient way to distinguish growth-oriented entrepreneurs from small business owners with other motivations for having entered self-employment. A related distinction explored by Davis et. al. (2009) is the distinction between small businesses that employ workers (employer businesses) vs. non-employer businesses. Davis et. al.

(2009) find that about 30 percent of all new employer businesses start as nonemployer businesses, with the nonemployer businesses that transition to being employer businesses having larger and much faster-growing revenues than other nonemployer businesses.

An important theme in the literature on self-employment is the role of liquidity constraints in individuals' decisions to start a business. Evans and Jovanovic (1989) present evidence that wealthier individuals are more likely to become entrepreneurs. Hurst and Lusardi (2004) note, however, that the accumulation of wealth may not be exogenous. Using information on inheritances to instrument for wealth, they find that both past and future inheritances seem to matter for the odds of becoming self-employed, suggesting that the relationship between wealth and self-employment may reflect something other than the role of liquidity constraints. Fairlie and Krashinsky (2012) question that conclusion, arguing that it is important to distinguish between job losers and non-job losers in analyzing entry into self-employment and demonstrating that, within each of those two groups, wealth is positively related to entry into self-employment.

Many existing studies of the decision to enter self-employment identify whether a person is self-employed based on the responses to questions asked in a household survey. Self-employment typically is treated as an alternative to wage and salary employment, so that a person can be categorized as holding one or the other of those statuses, but not both. In earlier work comparing household survey responses to tax records for the same individuals, we have found that, in a significant number of cases, household survey data fail to identify self-employment activity that appears in tax records. Many but not all of the individuals whose self-employment activity is not captured in household survey data are engaged in self-employment as a secondary activity (Abraham et al. 2017). In another analysis based on tax data, Jackson, Looney and Ramnath (2017) report that the share of tax filers with sole proprietor income increased between 2000 and 2014 both among those with and among those without wage and salary earnings.

The introduction of a variety of online platforms for matching workers to customers who need a particular service may have made it easier for individuals to take on short-term projects that make use of their skills, either as their primary labor market activity or as a secondary activity undertaken in conjunction with wage and salary work. With an online platform, a person does not have to invest in locating customers, meaning that the barriers to entry into self-employment are lower. Several recent studies have used Uber's records on its driver-partners to examine how they are using the Uber online ridesharing platform. Hall and Krueger (2018) observe that many drivers are active on the Uber platform only for a short period. Data from surveys of Uber drivers also cited in their paper indicate that a majority of the drivers who responded combine driving for Uber with full-time or part-time work on another job. Cook et al. (2018) are concerned primarily with the gender gap in Uber drivers' earnings, but also document the high rates of attrition on the platform for both men and women.

Other studies have examined gig employment activity using transactions-level data captured by bank and credit card records (Farrell and Greig 2016a, 2016b) or personal financial management software that assists individuals in tracking their income and spending (Koustas 2018). In their analysis, Farrell and Greig (2016a, 2016b) are able to identify payments facilitated through any of a list of online platforms and observe how those payments fit into individuals' streams of income from other sources. Similar to the findings based on analysis of rideshare company data, Farrell and Greig (2016b) find that more than half of online platform participants end their careers within twelve months. Farrell and Greig (2016a) document that, in months when wage and salary income dips, online platform participants are able to substantially offset those declines with platform earnings. Koustas (2018) analyzes data for the users of one company's online personal financial management software that also captures transactions-level information. In a sample of individuals who can be identified as receiving regular bi-weekly paychecks, he finds that work as an Uber

driver mitigates fluctuations in pay and allows drivers to smooth their consumption. He is able to examine earnings from driving net of gasoline purchases and current car service or repair expenses.

While much has been learned from the studies just described, they also have limitations. The rideshare company data used in several studies offer an in-depth look at individual rideshare drivers' interactions with that company, but do not contain the information that would be needed to place those interactions into the broader context of drivers' full set of work activities. Studies that make use of financial records held by a financial institution or financial services firm may provide a broader perspective on covered individuals' sources of income, but the people for whom these records are available may not be representative of the population of interest. In addition, if people maintain accounts with more than one bank, do not link all of their financial accounts to their personal financial management software or use cash for some transactions, the data may not be comprehensive. Further, if individuals must incur expenses in order to earn money via an online platform, deposits of payments for work done through the app may overstate the net amount that is actually earned. Koustas (2018), for example, is able to subtract expenses he observes for gas and car service or repair in determining the net earnings of rideshare drivers, but he is not able to account for the effect that added driving may have in depreciating the value of a driver's vehicle.

This paper contributes to the literature by providing a broad look at sources of both wage and self-employment income among incumbents and entrants to an industry that has been transformed by the introduction of online platform apps that match service providers to customers. Our data come from information on self-employment income and wage and salary earnings reported to tax authorities. Because our data cover almost the entire population and essentially all of the labor income earned by each member of that population, our analysis is largely immune to the concerns about completeness and representativeness that might be raised about analyses based on data derived from bank or personal financial management software records. The information about

self-employment income and expenses reported to tax authorities also may provide a more accurate picture of the true net contribution of self-employment activity to household incomes. We turn now to a description of the data that are used in our analysis.

### III. Data

Our analysis rests on the microdata that underlie the Nonemployer Statistics (NES) published by the U.S. Census Bureau.<sup>6</sup> We supplement the nonemployer microdata with information on wage and salary earnings from the Longitudinal Employer-Household Dynamics (LEHD) program and demographic information from the Census Bureau's Individual Characteristics File (ICF).

Nonemployers are defined as businesses that have no paid employment or payroll, are required to file a federal income tax return, and have business receipts of \$1,000 or more (\$1 or more for the Construction sector). Most nonemployers are self-employed individuals operating as unincorporated sole proprietors, but there are also nonemployer businesses organized as corporations, S-corporations and partnerships. Nonemployer statistics originate from Schedule C's (for unincorporated sole proprietors) and other tax forms providing similar information that are filed with the Internal Revenue Service. The Nonemployer Statistics are published for approximately 450 industries categorized according to the North American Industry Classification System (NAICS), at various levels of geography, and, since 2008, also for various types of Legal Form of Organization (LFO).

<sup>&</sup>lt;sup>6</sup> The U.S. Census Bureau publishes counts of nonemployers and their receipts at <a href="https://www.census.gov/programs-surveys/nonemployer-statistics.html">https://www.census.gov/programs-surveys/nonemployer-statistics.html</a>. The underlying microdata are a little used resource whose potential for better understanding the dynamics of labor market activity are just beginning to be appreciated; see, for example, Goetz et al. 2013, Goetz et al. 2017, and Hyatt, Murray and Sandusky 2018.

<sup>&</sup>lt;sup>7</sup> Note that the restriction in the official Nonemployer Statistics to individuals with business receipts of at least \$1,000 means that those with the most limited self-employment activity – for example, individuals who try ride-sharing for a short period of time but decide after a small number of rides that it is not for them – are excluded from our core dataset.

Figure 1 displays the total number of nonemployer businesses for each year from 1997 through 2016 and the number organized as sole proprietorships starting in 2008. In 2016, there were 24.8 million nonemployers with receipts of 1.17 trillion dollars. Of these, 21.5 million were sole proprietors, accounting for receipts of 0.73 trillion dollars. We are especially interested in nonemployers in NAICS 4853, Taxi and Limousine Services. As shown in Figure 2, after trending slowly upwards from 1997 through 2013, the number of nonemployers in this industry shot up sharply beginning in 2013. The number of self-employed drivers more than tripled between 2013 and 2016, growing from 223,814 drivers in 2013 to 700,565 drivers in 2016, an increase of 213 percent.<sup>8</sup>

There are many 4-digit NAICS industries for which published Nonemployer Statistics are not available, but NAICS 4853 accounts for over 80 percent of 3-digit NAICS 485, Transit and Ground Passenger Transportation, and the growth in that somewhat larger 3-digit industry can be compared to the growth in other 3-digit NAICS industries. NAICS 485 grew by 220 percent between 2013 and 2016, adding 597,349 nonemployer businesses. No other 3-digit industry has grown anywhere near so rapidly over this period. Excluding industries with fewer than 100,000 nonemployer businesses in 2013, the five 3-digit industries with the next highest growth rates in the published Nonemployer Statistics over the same period are NAICS 488, Support Activities for Transportation (43.5 percent growth and 50,136 additional nonemployer businesses); NAICS 492, Couriers and Messengers (22.5 percent growth and 36,698 additional nonemployer businesses);

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<sup>&</sup>lt;sup>8</sup> We also have examined an integrated micro database of CPS respondents matched to the nonemployer records. We find that most individuals with nonemployer activity in NAICS 4853 report no self-employment activity in the CPS. Moreover, this discrepancy has risen dramatically over time. The implication is that the increase in self-employment in NAICS 4853 is not being captured in the CPS.

<sup>&</sup>lt;sup>9</sup> Nonemployer statistics are published at the 3-digit level for all industries except NAICS 23 Construction, NAICS 42 wholesale trade and NAICS 51 Information, where information is reported at the 2-digit industry level (NAICS 23 and 42) or for the portion of the 2-digit industry that remains after reporting for selected 3-digit industries (NAICS 51).

NAICS 611, Educational Services (16.4 percent growth and 100,972 additional nonemployer businesses); NAICS 446, Health and Personal Care Stores (15.6 percent growth and 23,347 additional nonemployer businesses); and NAICS 484, Truck Transportation (14.5 percent growth and 74,381 additional nonemployer businesses). While some of the growth in these industries may be due to activities in which matching of buyers to sellers of services is mediated online, they are not industries that are an obvious fit with the popular perception of the gig economy and their growth has in any case been far less dramatic than the growth in the ridesharing industry.

The reason for presenting the sole proprietor series in Figures 1 and 2 is that we have the microdata to replicate these numbers. As of this writing, our analysis is based on microdata for 2010 and 2012-2015. Each record in the microdata file contains information on gross receipts and expenses as reported on a business's Schedule C for the year in question. The microdata record also contains a unique identifier for the owner of the business, the Census Bureau's protected identification key (PIK). Knowing the PIK of the business owner allows us to add information on wage and salary earnings from the LEHD and demographic information from the ICF to the nonemployer information just described.

Our analysis focuses on the person as the unit of observation. In the microdata used to produce the published nonemployer sole proprietor statistics, however, the unit of observation is the Schedule C (i.e., the business) and there are some people who file multiple Schedule C's (i.e., have more than one business). Our first step in preparing the nonemployer microdata for analysis is thus to collapse the data to one record per individual per year, such that each record contains information for all of the businesses that a person may have operated in that year. We restrict the

<sup>&</sup>lt;sup>10</sup> NAICS 485 also dominates over the 2010-16 period with a growth rate of 298%. The next five industries listed in this paragraph are also in the top seven growth industries for the 2010-16 period. NAICS 488 exhibits growth of 57 percent over this longer period. The top seven also include NAICS 448 (Clothing and Clothing Accessory Stores) and NAICS 711 (Performing Arts, Spectator Sports, and Related Industries).

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. As shown in Table 1, the time series patterns of both all nonemployers and nonemployers in NAICS 4853 are similar in our analytic sample to that in the published statistics.

We next add information on wage and salary earnings to the nonemployer information just described. This wage and salary information comes from the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) data, which is sourced from state Unemployment Insurance (UI) administrative records. The coverage of the LEHD is all private sector employers subject to state UI coverage (approximately 98 percent of private sector employment), plus state and local government employment. Federal government employees are the major group of wage and salary earners omitted from the LEHD. We have information on LEHD earnings quarterly for individuals in all 50 states plus the District of Columbia for each year from 2012 through 2015.

The final step in creating our core data infrastructure is to incorporate demographic information from the 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. An education variable also is included on the ICF, though it is imputed for about 80 percent of individuals and missing for about another five percent. In all of the analyses that follow, we exclude individuals for whom gender, date of birth, race, ethnicity or place of birth are missing. The information on race is used to create a dummy variable for nonwhite and the information on place of birth is used to create a dummy variable for foreign born. We restrict our sample to individuals who, based on their birth dates, are 14 to 99 years old in a given year. Because we have a unique individual identifier, we are able to link individuals' records over time. This means that, starting in 2013, we are able to determine whether any given nonemployer is an incumbent (someone who was a nonemployer in the previous

year) or an entrant (someone who was not a nonemployer in the previous year). We also are able to observe exits from nonemployer self-employment. Similarly, by linking the quarterly wage records from the LEHD over time, we are able to observe movements into and out of wage and salary employment.

In some of the analysis that follows, we will be interested in the earnings of nonemployer sole proprietors. The discussion in this draft focuses on net receipts – gross receipts minus the expenses claimed on an individual's Schedule C – as the measure of nonemployer earnings. According to a guide for rideshare drivers published by H&R Block, allowable expenses include any fees deducted from gross fares by a ridesharing company and the cost of operating the driver's vehicle, as well as items such as tolls and parking charges paid while working as a rideshare driver, a prorated share of auto loan interest or personal property taxes on the vehicle, and refreshment provided to the passenger. 11 Costs of operating the vehicle may be determined based either on applying the IRS-approved mileage cost rate, which varied between 55.5 cents and 57.5 cents per mile from 2012 through 2015, or on actual expenses. To the extent that claimed expenses represent true costs associated with earning self-employment income, net receipts is the measure that corresponds most closely to the earnings received by a wage and salary worker, though it should be noted that, because those who are self-employed must pay both the employer and the employee shares of Social Security and Medicare taxes, a dollar of self-employment income nets the individual less than a dollar of wage and salary income. For many drivers, however, the short-term out-of-pocket cost of driving their car may be well below allowable expenses calculated using the IRS-approved mileage rate. To the extent that a rideshare driver cares primarily about the amount she takes home each week as a means of smoothing temporary fluctuations in other income, the

<sup>&</sup>lt;sup>11</sup> See <a href="https://www.hrblock.com/pdf/Partner-Facing-Guide-FAQ-Combined.pdf">https://www.hrblock.com/pdf/Partner-Facing-Guide-FAQ-Combined.pdf</a>.

most salient earnings figure may be gross receipts minus immediate expenses, which we would expect generally to lie somewhere between gross receipts and net receipts. Some information about gross receipts is reported in this draft of the paper and we plan to look more closely at their behavior in the next draft.<sup>12</sup>

## IV. Changes in the Taxi and Limousine Services Industry

Individuals may choose to work in Taxi and Limousine Services for any of a variety of reasons. For some people, working as a taxi or rideshare driver may be a primary source of income. For many people, however, working as a driver in this industry may increasingly serve a different purpose—to provide earnings that smooth temporary fluctuations in other income (Farrell and Grieg 2016a, Koustas 2018), to supplement other income, to ease the transition from being out of the labor force to regular employment or, at the end of the work life, to ease the transition from regular employment to fully retiring. These different reasons for becoming a driver in NAICS 4853 carry different implications for the patterns of earnings, entry into the industry and subsequent exit from the industry. We would expect, in particular, for the patterns for those for whom driving is a primary source of income as an incumbent to look quite different from the patterns for those entering the industry as online platform ridesharing becomes available. With this broad framework for thinking about how individuals may use driving mediated by an online platform ridesharing company—or indeed self-employment more generally—in mind, we turn to an examination of the nonemployer data we have assembled.

Table 2a presents descriptive statistics for sole proprietors in NAICS industry 4853, Taxi and Limousine Services for the years from 2013 through 2015. Because we are especially interested

<sup>&</sup>lt;sup>12</sup> Similar remarks about the role of expenses for traditional taxi drivers apply to the difference between gross and net receipts.

in the industry's evolution over this period, these statistics are shown separately for entrants and incumbents. Entrants are defined as individuals who earned no income as nonemployers in NAICS 4853 in the previous year; incumbents are those with earnings in the prior year in NAICS 4853. As even a cursory examination of Table 2a makes clear, entrants to NAICS 4853 look very different than incumbents. They are considerably more likely to be young and female, and considerably less likely to be foreign-born and nonwhite. Entrants also are much more likely than incumbents to have wage and salary earnings along with nonemployer earnings during the year. In addition, both gross receipts and net receipts are considerably lower for entrants than for incumbents.

These differences between entrants and incumbents are in part a natural consequence of life cycle dynamics. Self-employed incumbents in any industry naturally will tend to be older than self-employed entrants. To the extent that those who enter self-employment either succeed in building up their earnings over time or choose to exit, one also would expect entrants to self-employment to earn less on average than incumbents. Further, to the extent that it is common to work as an employee before entering self-employment, it also would be common for entrants to have both wage and salary income and self-employment income in the year they transition to self-employment. Such dynamics, however, cannot explain the large changes in the characteristics of entrants to NAICS 4853 that we observe in our data during the period when the number of nonemployer sole-proprietors in this industry is surging.

Comparing entrants in 2015 to entrants in 2013, the share who are female increases by 5.6 percentage points, the share aged 14-34 years old increases by 5.9 percentage points, the share who are foreign born decreases by 20.8 percentage points, and the share who are non-white decreases by 9.2 percentage points. Perhaps most interesting, the share of NAICS 4853 entrants who have wage and salary earnings in their year of entry rises by 20.6 percentage points over just this two year period. Average annual gross and net receipts fell modestly from 2013 to 2015 for incumbents (by

8.2 percent and 12.1 percent, respectively), but gross receipts for entrants fell by 46.3 percent and net receipts by 58.6 percent over the same period. These patterns are consistent with a growing share of entrants in NAICS 4853 not using it as a primary source of support. Interestingly, the average wage and salary earnings of entrants who combine driving with wage and salary work in the year of entry was substantially higher (by 42.8 percent) in 2015 than in 2013.

Table 2b presents analogous statistics for sole proprietors in industries other than NAICS 4853. Self-employment in other industries is more female, less foreign-born and less nonwhite than self-employment in NAICS 4853. More relevant for our analysis, entrants and incumbents are considerably more similar along these dimensions than are entrants and incumbents in NAICS 4853. The most noticeable demographic difference between self-employed entrants and self-employed incumbents outside of NAICS 4853 is that, similar to NAICS 4853, entrants tend to be younger than incumbents. Entrants also have lower gross and net receipts than incumbents and are more likely to have wage and salary income in the year of entry than incumbents in the same year. None of this is terribly surprising. In contrast to NAICS 4853, however, the characteristics of entrants to self-employment in other industries have changed little and the differences between self-employed entrants and incumbents have been quite stable. In other words, outside of NAICS 4853, self-employment has not exhibited the dramatic changes that are so apparent in NAICS 4853.

We are especially interested in the increasing share of nonemployer entrants to NAICS 4853 who also have wage and salary earnings. One thing we would like to know is whether this change can be explained by changes in the characteristics of those who are doing this work. To gain further perspective, we estimate simple descriptive regressions with a dependent variable equal to one if a nonemployer sole proprietor also has wage and salary income in a given year and zero otherwise. These models are fit using data on both incumbents and entrants from 2013 through 2015. Table 3a reports the coefficients from models for those with earnings as a nonemployer sole proprietor in

NAICS 4853; Table 3b reports the same set of coefficients for those with nonemployer sole proprietor earnings in other industries (but not NAICS 4853). The first two columns in each table include only dummy variables differentiating between incumbents and entrants by year; columns (3) and (4) add controls for worker characteristics. The coefficient estimates reported in column (1) replicate the numbers from Table 2a or Table 2b on the share in each group by year who have wage and salary income; those in column (2) capture exactly the same information but highlight the differences between entrants by year and incumbents in later years compared to those who were incumbents in 2013, just before the start of the period of rapid growth in nonemployer activity in NAICS 4853.

Turning first to Table 3a, those who entered NAICS 4853 as nonemployer sole proprietors in 2013 were 34.4 percentage points more likely than 2013 incumbents to have both wage and salary earnings and nonemployer earnings during the year. The share of entrants with wage and salary earnings rose significantly over the next two years and 2015 entrants were 55.0 percentage points more likely than 2013 incumbents to have earnings from both sources, an increase of 20.6 percentage points. <sup>13</sup> Columns (3) and (4) add controls for worker characteristics, allowing us to assess how much of this widening gap between entrants and the 2013 incumbents can be attributed to observable composition changes. Controlling for gender, age, foreign born, race and ethnicity reduces the percentage point difference between the shares of 2013 entrants and 2013 incumbents with wage and salary income from 34.4 to 28.8 percentage points and reduces the difference for 2015 entrants compared to 2013 incumbents from 55.0 to 45.7 percentage points. Holding observable characteristics constant, the implied increase in the fraction of drivers who had wage

<sup>&</sup>lt;sup>13</sup>The gap in the probability of having both ridesharing and wage earnings between entrants and incumbents in the same year also grew between 2013 and 2015, but given the large growth in the number of nonemployers in the industry, by 2015 many of those we label as incumbents are themselves relatively recent entrants.

and salary income in their entry year is only modestly smaller than in the model with no controls, a 16.9 percentage point increase in the model with controls (45.7 minus 28.8) rather than 20.6 percentage points (55.0 minus 34.4). Adding education to the model has little effect on this estimated increase. <sup>14</sup> These results imply that little of the rising propensity of entrants to NAICS 4853 to combine income from driving with wage and salary earnings is attributable to changes in the demographic composition of drivers, suggesting that it is the nature of work in the industry that has changed.

The contrasting patterns for self-employed workers in other industries are shown in Table 3b. The difference between entrants and incumbents in the propensity to have wage and salary income is much smaller in other industries and has increased only very modestly over time; outside of NAICS 4853, 2015 entrants are just 3.1 percentage points more likely than 2013 entrants to have wage and salary income in the same year. The controls for worker characteristics added in columns (3) and (4) account for some of the difference between entrants and incumbents, but the effects for 2015 entrants are very similar to those for 2013 entrants and the difference between them is little changed.

Another way to gain insights into how the new entrants to NAICS 4853 are using work in this industry is to look at the changes in their earnings in the year they enter the industry. Table 4a provides descriptive statistics on over-the-year changes in the earnings of entrants and (for comparison) incumbents in NAICS 4853, disaggregated by their wage and salary earnings status. Table 4b reports the same descriptive statistics for nonemployer entrants and incumbents in other industries. The four possibilities with regard to workers' wage and salary status are (1) having wage

<sup>&</sup>lt;sup>14</sup> We report results controlling for worker characteristics with and without education because education is imputed or missing for a large fraction of individuals. Available evidence suggests that the education imputation does a relatively good job of yielding an appropriate ranking of educational attainment across individuals for a given year but less precision for specific education categories.

and salary earnings in both the prior year and the current year (W&S Stayer); (2) having wage and salary earnings in the prior year but not the current year (W&S Exiter); (3) having wage and salary earnings in the current year but not the prior year (W&S Entrant); and (4) having no wage and salary earnings in either year (No W&S).

As can be seen in Table 4a, by 2015, the group that we refer to as W&S Stayers accounted for a full two-thirds of entrants to NAICS 4853 and those we term W&S Exiters accounted for another 8.4 percent. Put slightly differently, by 2015, three-quarters of entrants to NAICS 4853 had prior year wage and salary income. As recently as 2013, this was true for only 58.5 percent of entrants. Entrants to NAICS 4853 without current or prior-year wage and salary income represented about 35.3 percent of entrants in 2013, but that share had fallen to just 18.9 percent of entrants by 2015. A quick look at Table 4b reveals that no such changes have occurred among entrants to self-employment elsewhere in the economy.

In each year from 2013 through 2015, the average entrant to NAICS 4853 who had both prior year and current year wage and salary income experienced a decline in their wage and salary earnings in the year they entered ridesharing, though the size of this decline has fallen over time. Net receipts for this group of entrants have been modest and also have fallen over time, averaging \$3,446 in 2013 and only \$1,246 in 2015. In 2015, net receipts offset only about half of the same-year decline in wage and salary earnings for this group. Looking at the corresponding panel in Table 4b, the approximately 60 percent of entrants to self-employment outside of NAICS 4853 who had continuing wage and salary income also experienced a decline in their wage and salary earnings, but the increase in these individuals' net self-employment receipts was larger, averaging about \$6,000 in each of the three years for which we have data and more than offsetting the loss in wage and salary earnings. While this is not causal evidence, it is consistent with W&S Stayers who take up self-employment in NAICS 4853 being pushed into doing so by a loss in their wage and

salary earnings, but W&S Stayers who take up self-employment in other industries being more positively drawn into self-employment.

A similar story seems to fit the patterns observed for a second smaller group of entrants to NAICS 4853 self-employment, those who had wage and salary earnings in the prior year but none in the year they entered self-employment. As can be seen in Table 4a, net nonemployer receipts for this group of entrants averaged \$6,031 among the 2015 cohort, down from \$8,797 in 2013, and offset just 43 percent of the loss in these entrants' wage and salary earnings, a smaller share than in either 2014 or 2013. In contrast, as can be seen in Table 4b, the net self-employment receipts of those leaving wage and salary employment for self-employment in other industries in 2015 averaged \$13,680, similar to 2014 and about \$1,000 more than in 2013, and offset about 70 percent of lost wage and salary earnings.

The third panel of Table 4a displays information for those who enter wage and salary employment in the same year that they also take up self-employment activity. This is a small group, accounting for only about 6 percent of entrants to NAICS 4853 in all three years, similar to the share among entrants to self-employment in other industries. These may be people who are self-employed during a transition to holding a wage and salary job or who combine the two in some other way. In any case, entrants to NAICS 4853 in this group have modest net receipts that have become smaller for successive entry cohorts, falling from \$5,547 for the 2013 cohort to \$3,008 for the 2015 cohort. In 2015, net receipts accounted for just 28.1 percent of this group's total earnings in their year of entry into NAICS 4853.

A final group of NAICS 4853 entrants are those without current or prior wage and salary income. Those in this group earn a relatively modest amount from their nonemployer activity in NAICS 4853 and that amount has fallen over time, from \$9,105 in 2013 to \$5,667 in 2015. Further, a fraction of those who enter NAICS 4853 are leaving other self-employment work, meaning that

the increase in their total earnings is less than the amount they add in NAICS 4853 earnings. In 2015, for example, the average NAICS 4853 entrant in this group had earnings of about \$5,667 but an increase in their total earnings of just \$4,084. In contrast, those entering self-employment in other industries who do not have prior or current wage and salary earnings, shown in the fourth panel of Table 4b, have substantially higher net receipts from self-employment, averaging about \$18,000 across the three years and not exhibiting any obvious trend.

As with the propensity to combine wage and salary work with self-employment, we are interested in whether and to what extent changes in the composition of the entrant populations might explain these patterns of change in earnings at entry. Table 5a reports descriptive regressions of the year-over-year within-individual growth in total earnings for nonemployer sole proprietors in NAICS 4853 by individuals' status as a nonemployer entrant versus nonemployer incumbent crossed with their wage and salary employment status (W&S Stayer, W&S Exiter, W&S Entrant or No W&S). Similarly specified regressions are reported in Table 5b for nonemployer sole proprietors in other industries. In each of these tables, column (1) reports regressions with earnings in dollars as the dependent variable and replicates the total earnings numbers shown in either Table 4a or Table 4b. In the remaining columns, the dependent variable is IHS earnings, where IHS(x) =  $\ln(x + \operatorname{sqrt}(1+x^*x))$ . Column (2) is specified in the same way as column (1), with a dummy variable for each group of interest; column (3) includes a constant term, with all effects estimated relative to incumbents with no wage and salary income; and columns (4) and (5) add the same lists of demographic controls as in Table 3a and Table 3b (gender, age dummies, and indicators for race, ethnicity and foreign born, and then the same variables plus education).

The results confirm that changes in demographic composition do not explain the patterns of earnings change that we observed in the descriptive statistics for NAICS 4853 reported in Table 4a. Even after controlling for demographics, NAICS 4853 entrants who had previous wage and salary

earnings experience a decline in their total earnings in the year they enter. For those who exit wage and salary work entirely, the size of this decline has become larger over time. Entrants with wage and salary income neither in the prior year nor in the current year have modest net receipts that have become smaller with each successive cohort. All of these patterns are robust to controlling for worker characteristics.

In contrast, consistent with Table 4b, the analogous panels in Table 5b show marked stability in the patterns of earnings change associated with entry into nonemployer activity outside of NAICS 4853, both in the models with no controls and in the models that add controls for worker characteristics.

To the extent that entrants to NAICS 4853 increasingly are using earnings from driving to cushion fluctuations in income from other sources or as a supplement to other income, as opposed to viewing driving on its own as a means of earning a livelihood, we might expect them to have become less attached to the industry. Table 6a presents simple descriptive regressions for survival rates for recent entrants into NAICS 4853, which can be contrasted with the similar descriptive regressions for entrants into self-employment in other industries shown in Table 6b. In these regressions, we define an entrant as someone who was not working in NAICS 4853 (Table 6a) or was not a nonemployer in another industry (Table 6b) two years earlier (in 2010 for those observed as self-employed in 2012 or in 2012 for those observed as self-employed in 2014). The dependent variable is an indicator variable for whether the person remained in self-employment in the following year (2013 or 2015). Both in NAICS 4853 and in other industries, a large fraction of those who enter self-employment over a two-year period do not remain in the following year.

<sup>&</sup>lt;sup>15</sup> The choice of years included in these regressions is dictated by the limitations of our current data infrastructure, which consists of data for 2010 and 2012-2015. Richer specifications will be possible once data for 2011 and 2016 have been added..

Between 2012 and 2014, the share remaining fell significantly. As can be seen in columns (1) and 2) of Table 6a, NAICS 4853 entrants in 2014 were five percentage points less likely to remain in the industry in the subsequent year than entrants in 2012. In contrast, there has been no such change in the survival rate for recent entrants to other nonemployer activity over the same period (columns (1) and (2) of Table 6b). Putting the results for NAICS 4853 somewhat differently, the share of recent entrants who had exited by the following year rose from 34.2 percent to 39.2 percent, an increase in the exit rate of 14.7 percent. About 30 percent of the decline in survival rates for recent entrants is attributable to changes in their demographic composition (columns (3) and (4)). Controlling further for net receipts and the presence of wage and salary earnings accounts for another 30 percent of the decline; as one might expect, entrants with lower net receipts or who had wage and salary earnings are more likely to exit. Even after all of these controls have been introduced, however, recent entrants as of 2014 appear to be less likely to stick with NAICS 4853 than recent entrants as of 2012.

To sum up, our descriptive findings demonstrate that the Taxi and Limousine Services industry is different on a number of dimensions. First, it is the industry with by far the most dramatic increase in nonemployer activity in the 2010-2015 period. Second, the characteristics of recent entrants to this industry are quite different from those of industry incumbents. They are much more likely to be female, younger, and U.S. born and less likely to be nonwhite. They also are much more likely than industry incumbents to combine wage and salary activity with their nonemployer activity and that difference grew sharply between 2013 and 2015 as new entrants surged into the industry. In contrast, except with respect to age, entrants to self-employment outside of NAICS 4853 look much more similar to incumbents and this has not changed over time.

The evidence is consistent with more recent entrants to NAICS 4853 using this activity as a flexible, part-time earnings opportunity. This is evident in the relatively low and declining earnings

of successive cohorts of recent entrants. Although turnover in the industry was high even before the surge in entry, recent entrants also are less likely than entrants even two years earlier to stay in the industry. Again, this is in contrast to entrants to nonemployer activity in other industries, where there has been little change in survival rates.

## V. Push and Pull Factors for the Growth in Self-employment in NAICS 4853

Implicit in much of the discussion thus far is the question of what leads individuals to become nonemployer sole proprietors. To address that question, we need to be able to identify the population at risk of entry into self-employment. One way to identify the population at risk would be to use those for whom the Census Bureau has an Individual Characteristics File (ICF) record. As previously noted, an ICF record exists for everyone who ever applied for a Social Security Number (SSN). Because there are people who obtain an SSN but later leave the country, however, this would not be entirely satisfactory. Instead, we use the Census Bureau's Resident Candidate File (RCF) to establish the at-risk population.

The RCF lists everyone with a PIK that the Census Bureau has identified as currently resident in the United States. Residence information is obtained from various administrative sources. For cases with multiple residence addresses in a given year, the Census Bureau applies a preference weighting to determine the single best address for the person and year in question. <sup>16</sup> In addition to being restricted to individuals identified as current U.S. residents, the RCF has the additional advantage that it provides the current state and county of residence for everyone on the file, information that can be crosswalked to defined Core Based Statistical Areas (CBSA). This is

<sup>&</sup>lt;sup>16</sup> Graham, Kutzbach, and Sandler (2017) describe the source files and the creation of preference weights underlying the RCF.

useful because it allows us to merge in locality-specific information related to both push and pull factors that might help to explain entry into NAICS 4853.

On the push side, we have merged into our data infrastructure state-and-year specific information on the annual change in employment in the industry in which each individual with prior wage and salary employment previously worked. These numbers are derived from the BLS Quarterly Census of Employment and Wages (QCEW). 17 Using quarterly earnings data from the LEHD, we also are able to identify previously-employed individuals who experienced a displacement event during the prior year, defined as a separation from an employer at which there was a large quarter-over-quarter decline in employment in any of the four quarters of the year.

On the pull side, we have incorporated into the data infrastructure whether, and if so when, online platform based ridesharing became available in an individual's CBSA. Because online platform-based ridesharing has been introduced at different times in different areas, this provides us with useful variation in the accessibility of ridesharing work.

Push and pull factors likely interact. A displaced worker in a CBSA where ridesharing has become available has opportunities for self-employment that would not otherwise be available. Displaced workers in any market could enter NAICS 4853 by working as a traditional taxi driver, but the barriers to entry would be higher and the opportunities to work a flexible schedule would be more limited. Our estimating equations thus include terms that interact displacement with the availability of online platform ridesharing.

Our descriptive results also suggest that prior labor market status influences the patterns of entry into non-employer activity in NAICS 4853. We control for prior labor market status (differentiating among those who had wage and salary income in the prior year, had other self-

<sup>&</sup>lt;sup>17</sup> Results using this information will be added to the next draft of the paper.

employment income in the prior year, had both wage and self-employment income in the prior year, or did not work in the prior year) and further interact prior labor market status with the availability of online platform ridesharing as described further below.

Our basic regression specification for entry as a NAICS 4853 nonemployer is given by:

$$\begin{split} Y_{igt} &= X_{igt}'\beta + \delta_g + \delta_t + \gamma_1 Push_{igt-1} + \gamma_2 Pull_{igt} + \gamma_3 Pull_{igt} * Push_{igt-1} \\ &+ \sum_s (\lambda_s + \theta_s Pull_{igt}) LM_{s,igt-1} + \varepsilon_{igt} \end{split}$$

where:

 $Y_{igt} = 1$  if person *i* in geography *g* enters as a NAICS 4853 nonemployer sole proprietor in year *t*, 0 else

 $X_{iat}$  is a vector of demographic characteristics for person i in geography g in year t

 $\delta_q$  is a set of geographic (CBSA) fixed effects.

 $\delta_t$  is a set of year fixed effects

 $Push_{iqt-1} = 1$  if person i in geography g is part of a mass layoff in year t-1, 0 else

 $Pull_{igt}$  = number of years online platform ridesharing has been available to person i in CBSA g in year t, 0 if no online platform ridesharing (in the year of entry, this variable takes on the value of 1).

 $LM_{s,igt-1}$  is a set of dummies equal to 1 for various labor market statuses, 0 otherwise. For entry into NAICS 4853, dummies are included for three possible labor market statuses: (i) wage and salary (W&S) only in t-l; (ii) nonemployer income in other industries only in t-l; and (iii) both W&S and other nonemployer income in t-l. The base group is people with no labor market income in t-l.

The population at risk of entry into nonemployer activity in NAICS 4853 in year t is composed of any person i who is between 14 and 99 years old in year t and is not self-employed in ridesharing (NAICS 4853) in year t-1. Further details on the construction of the at-risk population are provided in the data appendix.

In the regressions we have estimated, our pull factor is defined based on public domain information as the number of years that online platform ridesharing activity has been available in the CBSA where an individual lives. To construct this variable, we use information on when the Uber online ridesharing platform first became available in the CBSA. While there are other ridesharing companies, we interpret the availability of the Uber online platform as a good indicator of the availability of online platform ridesharing activity more generally. Using a simple linear years-since-entry variable simplifies the estimation of the various interaction terms included in our full specification. We also have estimated fully flexible nonparametric specifications, not reported here, that contain separate dummies for each possible number of years since online platform ridesharing became available in a CBSA and the full set of interactions of these dummies with displacement and prior labor market status. The results based on this specification closely approximate those for the linear specification.

One important point to note is that ridesharing companies did not randomly select the markets in which they made their online platforms available, but rather chose them on the basis of the opportunities they offered. This means that there could be underlying differences in self-employment growth rates that are correlated with online ridesharing platforms becoming available in a given area. We address this potential bias by controlling for CBSA fixed effects.

For comparison purposes, we also estimate and report an analogous specification for entry into other nonemployer activity. The specifications for these models are largely the same, including the same push and pull factors as for NAICS 4853. One difference is that, in the models for entry into self-employment in other industries, we allow for only two lagged labor market statuses,

<sup>&</sup>lt;sup>18</sup> Uber is the clear market leader in the industry. 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 (see the data appendix for more details).

comparing individuals who had wage and salary employment in t-1 to individuals who did not work in t-1.

The regression results for entry into NAICS 4853 are reported in Table 7a and those for entry into other industries in Table 7b. Several different specifications are reported, leading up to the full specification that includes all of the push, pull and interaction terms as well as demographic controls. Column (1) includes only year dummy variables; column (2) adds measures of prior year labor force status; column (3) adds the displacement dummy variable; column (4) includes year dummies and years that online platform ridesharing has been available in a person's CBSA; column (5) adds back in the prior year labor force status and displacement dummy; column (6) includes all of these variables plus interactions of years of online platform ridesharing availability with prior labor force status and displacement; and the complete specification in column (7) adds demographic controls. All models are estimated as deviations from CBSA means. Virtually all of the reported coefficients are statistically significant.

One point to note is that direct comparisons between the coefficients in Table 7a and those in Table 7b could leave a misleading impression. Despite the rapid growth of online platform ridesharing, self-employment in Taxi and Limousine Services still represents only a small fraction of all self-employment and the unconditional mean probability of entering self-employment in NAICS 4853 is correspondingly much smaller than that for entering self-employment in other industries (0.054 percent versus 2.411 percent). As a result, the coefficients in Table 7a are generally smaller than the corresponding coefficients in Table 7b. The raw regression estimates in these tables are informative with respect to the sign and statistical significance of relationships in the data, but our discussion will focus primarily on their implications for the proportional impact of

<sup>&</sup>lt;sup>19</sup> Those with any nonemployer activity in the prior year are excluded from the at-risk group for Table 7b.

various factors on the rate of entry into self-employment, where the proportional impact is evaluated relative to the unconditional mean of the entry rate in question.<sup>20</sup> These results are displayed in Figures 3 through 5.

Starting at the left-hand sides of Table 7a and Table 7b, the column (1) results capture the sharp increase in the rate of entry into NAICS 4853 and the absence of any clear trend in the rate of entry into self-employment in other industries. Column (2) implies that, both in ridesharing and in other industries, those with prior-year work activity are more likely to enter self-employment than those who did not work in the prior year (the base group). Column (3) adds the dummy variable for displacement; both in NAICS 4853 and in other industries, having experienced a displacement leads to an increase in the probability of entering self-employment. Years since the entry of online ridesharing in the CBSA appears in column (4) with only year dummies and in column (5) along with the prior year labor force status and displacement dummies. This variable takes on a sizeable positive coefficient in the ridesharing entry equation but also a smaller positive coefficient in the equation for entry into other self-employment, a finding that has echoes in the more complete specifications reported in the next two columns.

Results for entry to NAICS 4853 based on our most inclusive specifications are reported in Table 7a in column (6), without demographic controls, and in column (7), with demographic controls; the t-statistics for the column (7) specification are reported at the far right of the table.

Adding demographic controls to the column (6) model has little effect on the coefficients of interest and we focus on the column (7) results. In this model, the omitted labor force group is those who were not employed in the prior year and lived in a CBSA without online platform ridesharing.

<sup>&</sup>lt;sup>20</sup> That is, we focus on  $(\frac{\Delta y}{\Delta x})/y$ . Since *x* variables for the main effects of interest are dummy variables or are specified in integers (years since online platform ridesharing becoming available), we are effectively computing the elasticity of the response of the entry rate to changes in the explanatory variable of interest.

Relative to that group, non-displaced individuals with any form of prior work activity who live in a non-ridesharing CBSA are *less* likely to enter NAICS 4853. Even in a CBSA without online ridesharing platforms, displacement raises the probability of entering NAICS 4853. The advent of online ridesharing platforms in a CBSA has a positive effect on the probability of entering NAICS 4853 for all groups that grows over time. The coefficient on the online ridesharing platform variable captures this effect for individuals who did not work in the prior year (and thus also could not have been displaced); the interactions of the online ridesharing platform variable with the displacement dummy and with the prior year labor force status dummies show that the positive effects of having access to an online ridesharing platform are even larger for displaced workers and for those who worked in the prior year. It is the effects for these groups that are driving the relatively large coefficient on the online ridesharing platform variable and the positive effects of having worked in the prior year in the models in columns (4) and (5) that did not include any interaction terms.

The analogous full specification results for entry to other nonemployer activity are reported in columns (6) and (7) of Table 7b. Focusing on the full specification results in column (7), the main effect of displacement is to increase the likelihood of entry into other non-employer activity while the main effect of having lagged wage and salary activity is to decrease the likelihood of entry. The main effect of advent of online platform ridesharing is small and not significantly different from zero. There are, however, small positive effects estimated for the terms capturing the interaction of this variable with lagged workforce activity and with displacement.

Figure 3 translates the results reported in Table 7a and Table 7b into estimates of the proportional effects of factors included in the model on the rate of entry to self-employment in NAICS 4853 as compared the rate of entry in other industries, defined in both cases relative to the unconditional mean of the relevant entry rate. Both main effects and interaction effects are reported.

The main effect of an additional year of online platform ride sharing activity in a CBSA yields an increase in the likelihood of entry into NAICS 4853 that is about 45 percent as large as the mean entry rate. This is the effect that is relevant for an individual who was not employed in the prior year (and thus could not have been displaced). In contrast, the main effect of an additional year of online platform ridesharing availability in a CBSA is very close to zero for the probability of entry to other nonemployer activity.

The main effect of displacement is to increase the probability of entry into NAICS 4853 by 4 percent relative to the mean rate of entry into NAICS 4853 and the probability of entry into other self-employment by 11 percent relative to the mean rate of entry for other industries. Thus, in the absence of online platform ridesharing in a CBSA, displacement yields a proportionally larger increase in the likelihood of entry into nonemployer activity in other industries than in NAICS 4853. Having prior year wage and salary activity is associated with a reduction in the probability of entry into NAICS 4853 that is 58 percent as large as the mean entry rate, compared to a reduction in the probability of entry into other industries of only about 4 percent. Workers who had wage and salary activity in the prior year are much less likely than those who did not work in the prior year to become taxi drivers in a CBSA in which online ridesharing platforms are not available.

The interactions between the online ridesharing platform variable and the displacement dummy imply that an additional year of online platform ridesharing activity in a CBSA increases the positive impact of being displaced on entry to NAICS 4853 by 16 percent and the positive impact of being displaced on entry to other industries by 5 percent, both relative to the mean rate of entry into the industry or set of industries in question. Similarly, an additional year of online platform ridesharing activity in a CBSA increases the probability of an individual with prior year wage and salary income entering NAICS 4853 by 40 percent relative to the mean entry rate, but by just 1 percent for other industries.

By design, the bars in Figure 3 that capture the effects of access to online ridesharing platforms show only the effects of such access having been available for one additional year. Building on Figure 3, Figure 4 illustrates the cumulative impact on entry for displaced workers of years since online platform ridesharing activity became available in their CBSA, both for entry into self-employment in NAICS 4853 and for entry into self-employment in other industries. The first data point on the left is "never entry," which corresponds to the main effect of displacement and is capturing the impact of displacement on entry for CBSA's with no online platform activity to date. The remaining values are calculating using both the main and interaction effects from Figure 3, incorporating the main effect for rideshare entry plus the main effect for displacement plus the effect associated with the interaction between rideshare entry and displacement.

In the first year of online platform ridesharing activity in a CBSA, being displaced raises the probability of entering NAICS 4853 by 64 percent relative to the mean entry rate. <sup>21</sup> This compares to an increase of just 4 percent for workers who are displaced in a CBSA without online platform ridesharing. The increase in the probability of entry into self-employment in other industries for those who are displaced is 16 percent as large as the unconditional mean entry rate in the first year of online platform ridesharing, compared to an increase for displaced workers of 11 percent in a CBSA without online ridesharing platforms. These effects cumulate, so that by three years after the advent of online ridesharing platforms in a CBSA, the increase in the rate of entry of displaced workers into self-employment in NAICS 4853 is about 2 ½ times as large as the unconditional mean entry rate.

Figure 5 presents the analogous cumulative effects for those with prior year wage and salary income compared to those with no prior year earnings. The "never" reported effects are the same as

<sup>&</sup>lt;sup>21</sup> The 64 percent calculation includes the combined impact of the main effects for displacement and the first year of online ridesharing activity along with the interaction effect.

the main effects for Figure 3. Only in the year after online platform ridesharing entry does the probability that those with prior year wage and salary income enter NAICS 4853 rise above the probability for those with no prior year earnings. At that point, the probability of entry for those with wage and salary income in the prior year is 112 percent larger than the unconditional mean, while it is 89 percent larger than the unconditional mean for those with no prior year earnings. In contrast, there is no meaningful effect associated with the interaction between years since the advent of online platform ridesharing and prior year labor market activity for entry into self-employment in other industries.

It might seem surprising that there is *any* effect of online platform ridesharing on entry into other nonemployer activity, but such an effect is apparent in the cumulative impact for displaced workers displayed in Figure 4. We speculate that this may be the result of increasing familiarity with online ridesharing platforms having a spillover effect on displaced workers who also become more likely to seek out other types of online platform work. That is, in CBSAs where online platform ridesharing activity has become established, it may have become more salient to workers that there are self-employment opportunities (including other online platform activities) potentially available to them as at least a stopgap source of earnings.

### VI. Conclusion

The favorite example both in the popular media and academic research of the rise of the gig economy is the increasingly ubiquitous presence of ridesharing companies. Our evidence suggests that the Taxi and Limousine Services industry (NAICS 4853) stands out not only with respect to its rate of growth but also with respect to the changing characteristics of the entrants to self-employment it has attracted and the way in which these entrants appear to be using work in the industry. Entrants to this industry have characteristics that are very different from those of industry

incumbents. They are increasingly more likely to be female, young, and U.S. born, and increasingly less likely to be non-white. Entrants also are increasingly likely to combine wage and salary income with receipts from self-employment. In contrast, the characteristics of entrants to nonemployer activity in other industries have changed little over time and their characteristics are much more similar to those of incumbents. In the year that they enter NAICS 4853, entrants with previous wage and salary income experience a drop in their earnings that is partially but not fully offset by net receipts from ridesharing. Those who did not work at all in the previous year earn a modest amount from nonemployer activity and the average net receipts realized by these entrants has been falling.

The final set of analyses we have reported look more directly at the factors associated with entry into NAICS 4853 self-employment as contrasted with entry into other forms of selfemployment. Two main findings emerge from that analysis. First, among displaced workers, time since the advent of online ridesharing platforms in a CBSA has a large and positive effect on the probability that a displaced worker will enter self-employment as a nonemployer sole proprietor in NAICS 4853. Second, time since the advent of online ridesharing platforms in an area also has a large positive effect on the probability that workers with prior-year wage and salary income will enter NAICS 4853 self-employment. These findings are consistent with the ridesharing industry providing new opportunities for flexible income-generating activity to a wide range of individuals. Given the relatively modest average earnings from this activity, however, there is little evidence that the typical worker is using ridesharing in the gig economy as a primary means of support. Further, the fact that years since the advent of online ridesharing platforms—rather than just the presence of online ridesharing platforms—seems to be what matters suggests that, similar to the slow diffusion of many other sorts of innovation, the effects of this particular innovation are taking time to play themselves out in the labor market.

It is useful to recall that nonemployers in the Taxi and Limousine Services industry are traditionally a low earnings group. In 2013, incumbents in this industry who had no wage and salary income averaged just \$13,580 in net receipts. At that time, most incumbents in the industry worked as traditional taxi drivers. Even with the dramatic surge in entry into this industry enabled by the advent of online ridesharing platforms, the provision of driving services is not an inherently high earnings activity. Instead, it appears that, with lower barriers to entry and more flexible work schedules, ridesharing companies have attracted a wider range of individuals to this relatively low paying industry.

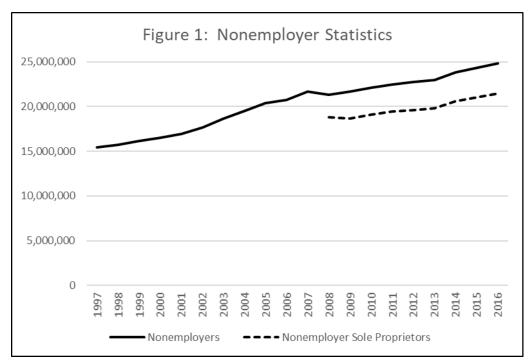
It is possible that online platforms in other industries are playing a similar role. We have not been able, however, to identify any other industry in which the role of online platforms is large enough as a share of the industry's activity to be readily discernible in the data. That said, the fact that the advent of online ridesharing platforms in an area seems to affect the rate at which displaced workers enter not just ridesharing self-employment but also self-employment in other industries may suggest that the role of online platforms elsewhere in the economy is becoming more salient to workers and especially to those who have experienced an economic setback.

## References

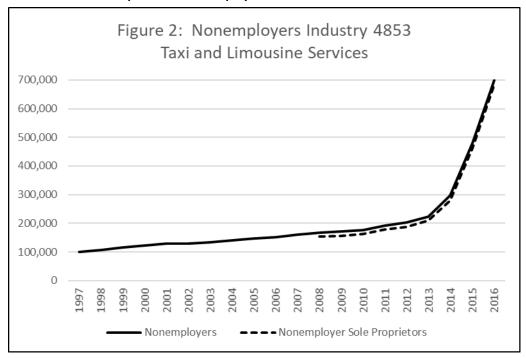
- Abraham, Katharine G., John Haltiwanger, Kristin Sandusky and James R. Spletzer. 2017. "The Gig Economy: Current Knowledge and Open Issues," Paper presented at the NBER/CRIW conference on *Measuring and Accounting for Innovation in the 21st Century*, Washington, DC. March.
- Alba-Ramirez, Alfonso. 1994. "Self-employment in the Midst of Unemployment: The Case of Spain and the United States," *Applied Economics*, 26, 189-204.
- Blanchflower, David G. 2000. "Self-employment in OECD Countries," *Labour Economics*, 7(5), 471-505.
- Blanchflower, David G. and Andrew J. Oswald. 2007. "What Makes a Young Entrepreneur?" IZA Discussion Paper No. 3139. November.
- Cook, Cody, Rebecca Diamond, Jonathan Hall, John A. List, and Paul Oyer. 2018. "The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers," unpublished working paper.
- 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.
- Evans, David S. and Boyan Jovanovic. 1989. "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints," *Journal of Political Economy*, 97(4), 808-827.
- Evans, David S. and Linda S. Leighton. 1989. "Some Empirical Aspects of Entrepreneurship," *American Economic Review*, 79(3), 519-535.
- Fairlie, Robert W. and Harry A. Krashinsky. 2012. "Liquidity Constraints, Household Wealth and Entrepreneurship Revisited," *Review of Income and Wealth*, 58(2), 279-306.
- Fairlie, Robert W. and Alicia Robb. 2007. "Families, Human Capital and Small Business: Evidence from the Characteristics of Business Owners Survey," *Industrial and Labor Relations Review*, 60(2), 225-244.
- Farrell, Diana and Fiona Greig. 2016a. "Paychecks, Paydays, and the Online Platform Economy," J.P. Morgan Chase Institute Report. February.
- Farrell, Diana and Fiona Greig. 2016b. "The Online Platform Economy: Has Growth Peaked?", J.P. Morgan Chase Institute Report. November.
- Goetz, Christopher, John Haltiwanger, Monica Garcia-Perez, and Kristin Sandusky. 2013. "Don't Quit Your Day Job: Using Wage and Salary Earnings to Support a New

- Business," CES Working Paper Series, 13-45.
- Goetz, Christopher, Henry Hyatt, Erika McEntarfer and Kristin Sandusky. 2017. "The Promise and Potential of Linked Employer-Employee Data for Entrepreneurship Research," in J. Haltiwanger, E. Hurst, J. Miranda and A. Schoar, *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, Chicago: University of Chicago Press, 433-462.
- 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.
- Hall, Jonathan and Alan Krueger. 2015. "An Analysis of the Labor Market for Uber's Driver-Partners in the United States," *ILR Review*, 71(3), 705-732.
- Hamilton, Barton H. 2000. "Does Entrepreneurship Pay? An Empirical Analysis of the Returns to Self-Employment," *Journal of Political Economy*, 108(3), 604-631.
- Hurst, Erik and Annamaria Lusardi. 2004. "Liquidity Constraints, Household Wealth, and Entrepreneurship," *Journal of Political Economy*, 112(2), 319-347.
- Hurst, Erik and Benjamin Wild Pugsley. 2011. "What Do Small Businesses Do?" *Brooking Papers on Economic Activity*, Fall 2011, 73-118.
- Hyatt, Henry, Seth Murray and Kristin Sandusky. 2018. "Business Ownership Dynamics and Labor Market Fluidity," unpublished working paper.
- Jackson, Emilie, Adam Looney, and Shanthi Ramnath. 2017. "The Rise of Alternative Work Arrangements: Evidence and Implications for Tax Filing and Benefit Coverage," Office of Tax Analysis Working Paper 114. January.
- Katz, Lawrence F. and Alan B. Krueger. 2016. "The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015," unpublished working paper.
- Koustas, Dmitri. 2018. "Consumption Insurance and Multiple Jobs: Evidence from Rideshare Drivers," mimeo.
- Levine, Ross and Yona Rubenstein. 2017. "Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More?" *Quarterly Journal of Economics*, 132(2), 963–1018.
- Rissman, Ellen. 2003. "Self-Employment as an Alternative to Unemployment," Federal Reserve Bank of Chicago WP 2003-34.
- Rissman, Ellen. 2006. "The Self-employment Duration of Younger Men over the Business Cycle," *Economic Perspectives*, 3Q, 14-27.

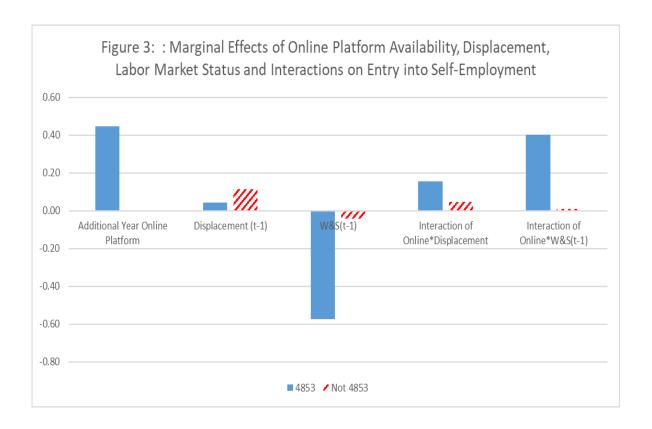
Taylor, Mark P. 1996. "Earnings, Independence or Unemployment: Why Become Self-Employed," *Oxford Bulletin of Economics and Statistics*, 58(2), 253-266.

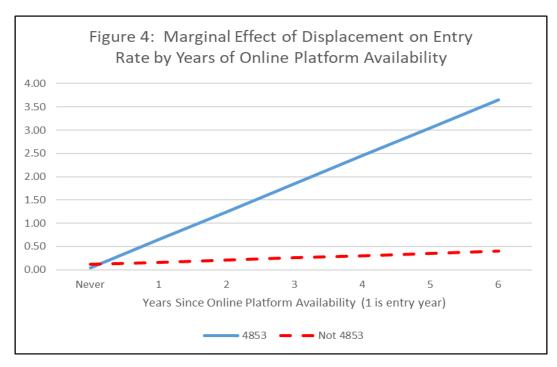


Note: Statistics from published Nonemployer statistics.



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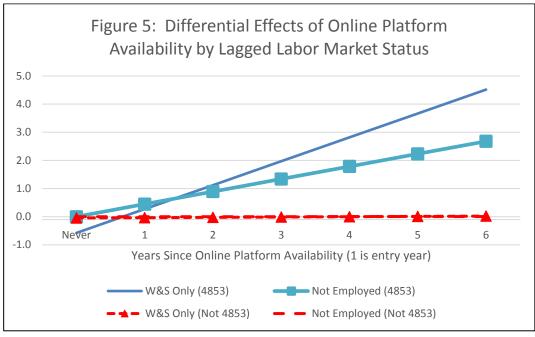


Table 1: Nonemployer Sole Proprietors, Published and Analytic Sample

	All Nonemployers,	All Nonemployers,
Year	Published	Analytic Sample
2012	19,634,605	18,540,000
2013	19,850,941	18,710,000
2014	20,592,806	19,320,000
2015	21,023,170	19,690,000

Notes: Published data are from the Census Bureau's website.

Analytic sample is defined in the text.

Analytic sample sizes are rounded to 4 significant digits.

	Industry 4853,	Industry 4853,
Year	Published	Analytic Sample
2012	187,788	178,000
2013	208,692	197,000
2014	279,417	263,000
2015	462,906	437,000

Notes: Published data are from the Census Bureau's website.

Analytic sample is defined in the text.

Analytic sample sizes are rounded to the nearest 1000.

Table 2a: Descriptive Statistics
Sample: Nonemployers in NAICS 4853: Taxi and Limousine Services

	Incumbents		Entrants			
	2013	2014	2015	2013	2014	2015
1 if 2010 NonEmp 4853	.6541	.5508	.4153	.1068	.0568	.0247
1 if Entrant to 4853	.000	.000	.000	1.000	1.000	1.000
1 if Incumbent to 4853	1.000	1.000	1.000	.000	.000	.000
1 if Female	.0618	.0641	.0731	.1547	.1680	.2113
1 if Age 14-20	.0005	.0005	.0007	.0081	.0076	.0072
1 if Age 21-24	.0098	.0111	.0144	.0512	.0595	.0725
1 if Age 25-34	.1404	.1495	.1708	.2694	.2989	.3082
1 if Age 35-44	.2523	.2517	.2558	.2670	.2690	.2570
1 if Age 45-54	.3080	.2977	.2796	.2293	.2090	.2020
1 if Age 55-64	.2197	.2184	.2098	.1359	.1206	.1151
1 if Age 65-99	.0693	.0711	.0690	.0391	.0354	.0380
1 if Foreign Born	.8322	.8357	.8099	.6890	.6207	.4808
1 if Nonwhite	.6115	.6141	.5982	.5370	.4988	.4450
1 if Hispanic	.1315	.1301	.1321	.1592	.1545	.1852
1 if Education 10	.1977	.1933	.1871	.1903	.1757	.1743
1 if Education 12	.2251	.2239	.2220	.2414	.2326	.2392
1 if Education 14	.2500	.2527	.2592	.2748	.2841	.2952
1 if Education 16	.2382	.2504	.2680	.2655	.2897	.2800
1 if Education Missing	.0889	.0797	.0638	.0280	.0179	.0113
Receipts 4853	41,840	42,020	38,410	21,340	16,160	11,450
Expenses 4853	29,680	30,010	27,720	15,090	11,780	8,860
Net Receipts 4853	12,160	12,010	10,690	6,250	4,380	2,590
1 if No W&S Earnings	.8234	.8018	.7244	.4795	.3563	.2736
Net Rcpts 4853   No W&	13,490	13,520	13,010	9,020	7,840	5,780
Non-4853 Net Rcpts   No	450	510	680	1,130	1,830	2,450
Total Earning   No W&S	13,950	14,030	13,690	10,160	9,670	8,230
1 if W&S Earnings	.1766	.1982	.2756	.5205	.6437	.7264
Net Rcpts 4853   W&S	5,940	5,880	4,610	3,700	2,460	1,390
Non-4853 Net Rcpts   W	490	500	550	390	590	500
W&S Earnings   W&S	22,330	23,300	26,460	21,470	26,690	30,660
Total Earning   W&S	28,760	29,680	31,620	25,560	29,740	32,550
Sample Size (Thousands)	139	153	191	58	110	246

Notes: Nonemployer sole proprietor data merged with ICF and LEHD wage and salary data.

Receipts, Expenses, and Net Receipts are in real dollars (GDP deflator, 2015=100).

Wage and salary (W&S) earnings are in real dollars (GDP deflator, 2015=100).

Total earnings are defined as W&S earnings plus nonemployer net receipts.

Average earnings are rounded to the nearest 10.

Table 2b: Descriptive Statistics
Sample: Nonemployers NOT in NAICS 4853: Taxi and Limousine Services

	Incumbents			Entrants			
	2013	2014	2015	2013	2014	2015	
1 if 2010 NonEmployer	.6723	.6001	.5431	.1758	.1780	.1636	
1 if Entrant	.000	.000	.000	1.000	1.000	1.000	
1 if Incumbent	1.000	1.000	1.000	.000	.000	.000	
1 if Female	.4459	.4480	.4494	.4717	.4696	.4741	
1 if Age 14-20	.0056	.0057	.0056	.0370	.0363	.0363	
1 if Age 21-24	.0259	.0264	.0260	.0861	.0846	.0844	
1 if Age 25-34	.1536	.1553	.1553	.2529	.2521	.2572	
1 if Age 35-44	.2130	.2102	.2075	.2214	.2186	.2193	
1 if Age 45-54	.2440	.2395	.2363	.1959	.1939	.1915	
1 if Age 55-64	.2176	.2177	.2195	.1371	.1416	.1385	
1 if Age 65-99	.1403	.1451	.1497	.0695	.0730	.0728	
1 if Foreign Born	.1982	.2011	.2026	.2079	.2039	.2057	
1 if Nonwhite	.1784	.1811	.1823	.2477	.2420	.2448	
1 if Hispanic	.1265	.1302	.1326	.1650	.1623	.1659	
1 if Education 10	.1377	.1392	.1394	.1638	.1597	.1598	
1 if Education 12	.2388	.2391	.2386	.2526	.2502	.2495	
1 if Education 14	.2765	.2775	.2785	.2910	.2917	.2926	
1 if Education 16	.2860	.2860	.2877	.2697	.2750	.2754	
1 if Education Missing	.0611	.0582	.0558	.0229	.0234	.0227	
Receipts	39,190	39,480	39,820	18,440	19,830	19,020	
Expenses	17,580	17,770	17,900	8,960	9,560	9,330	
Net Receipts	21,620	21,720	21,920	9,480	10,270	9,680	
1 if No W&S Earnings	.5714	.5684	.5645	.3595	.3491	.3282	
Net Receipts   No W&S	29,060	29,350	29,820	15,700	17,700	17,170	
1 if W&S Earnings	.4286	.4316	.4355	.6405	.6509	.6718	
Net Receipts   W&S	11,700	11,660	11,670	5,990	6,290	6,030	
W&S Earnings   W&S	46,610	46,650	47,800	36,920	37,960	39,210	
Total Earnings   W&S	58,310	58,310	59,470	42,920	44,240	45,240	
Sample Size (Thousands)	12,850	13,080	13,440	5,664	5,973	5,820	

Notes: Nonemployer sole proprietor data merged with ICF and LEHD wage and salary data.

Receipts, Expenses, and Net Receipts are in real dollars (GDP deflator, 2015=100).

Wage and salary \$ (W&S \$) are in real dollars (GDP deflator, 2015=100).

Total \$ are defined as wage and salary \$ (W&S \$) plus nonemployer receipts.

Average earnings are rounded to the nearest 10.

Table 3a: OLS Regressions, 2013-2015

Dependent variable = 1 if Nonemployer has Wage and Salary Earnings, 0 otherwise Sample: Nonemployers in NAICS 4853: Taxi and Limousine Services

	(1)	(2)	(3)	(4)
Intercept		.1766	.2164	.2246
1 if 2015 * Entrant 4853	.7265	.5498	.4571	.4424
1 if 2014 * Entrant 4853	.6437	.4670	.3956	.3816
1 if 2013 * Entrant 4853	.5205	.3439	.2883	.2767
1 if 2015 * Incumbnt 4853	.2756	.0989	.0903	.0840
1 if 2014 * Incumbnt 4853	.1982	.0215	.0209	.0184
1 if 2013 * Incumbnt 4853	.1766			
1 if Female			.0512	.0508
1 if Age 14-20			0542	0359
1 if Age 21-24			.0609	.0639
1 if Age 25-34			.0554	.0554
1 if Age 35-44				
1 if Age 45-54			0636	0568
1 if Age 55-64			1343	1152
1 if Age 65-99			2515	2199
1 if Foreign Born			1237	1178
1 if Nonwhite			0055	0048
1 if Hispanic			0140	0059
1 if Education 10				0223
1 if Education 12				
1 if Education 14				.0103
1 if Education 16				.0234
1 if Education Missing				2319
R-Squared		.2218	.2609	.2717

Notes: Mean of dependent variable is .4316. Sample size is 897,000.

All reported coefficients are statistically different from zero at the 1% level of significance. Demographic variables in columns 3-4 are entered as deviations from means.

Table 3b: OLS Regressions, 2013-2015

Dependent variable = 1 if Nonemployer has Wage and Salary Earnings, 0 otherwise Sample: Nonemployers NOT in NAICS 4853: Taxi and Limousine Services

	(1)	(2)	(3)	(4)
Intercept		.4286	.4407	.4453
1 if 2015 * Entrant	.6718	.2432	.2004	.1883
1 if 2014 * Entrant	.6509	.2223	.1801	.1683
1 if 2013 * Entrant	.6405	.2119	.1681	.1567
1 if 2015 * Incumbent	.4355	.0069	.0099	.0072
1 if 2014 * Incumbent	.4316	.0030	.0045	.0031
1 if 2013 * Incumbent	.4286			
1 if Female			0203	0217
1 if Age 14-20			0154	.0147
1 if Age 21-24			.0856	.0988
1 if Age 25-34			.0496	.0568
1 if Age 35-44				
1 if Age 45-54			0364	0295
1 if Age 55-64			1123	0925
1 if Age 65-99			3065	2621
1 if Foreign Born			0967	0857
1 if Nonwhite			.0465	.0513
1 if Hispanic			0032	.0165
1 if Education 10				0349
1 if Education 12				
1 if Education 14				.0310
1 if Education 16				.0768
1 if Education Missing				3813
R-Squared		.0424	.0947	.1294
Notes: Maan of dependent variable	ic 5002 Com	nla siza is 56	220.000	

Notes: Mean of dependent variable is .5003. Sample size is 56,830,000.

All reported coefficients are statistically different from zero at the 1% level of significance. Demographic variables in columns 3-4 are entered as deviations from means.

Table 4a: Descriptive Statistics
Sample: Nonemployers in NAICS 4853: Taxi and Limousine Services

		Incumbents			Entrants	
	2013	2014	2015	2013	2014	2015
W&S Stayer	.1349	.1544	.2238	.4581	.5817	.6667
Gross Receipts 4853	25,500	25,480	21,460	15,050	11,290	8,450
Net Receipts 4853	5,056	4,953	3,823	3,446	2,277	1,246
Net Receipts non-4853	514	499	535	359	524	432
W&S Earnings	26,820	27,630	30,540	23,410	28,620	32,550
Total Earnings	32,390	33,080	34,900	27,210	31,430	34,230
ΔGross Receipts 4853	2,756	4,108	3,819	15,050	11,290	8,450
ΔNet Receipts 4853	684	963	804	3,446	2,277	1,246
ΔNet Receipts non-4853	86	74	33	-211	-20	6
ΔW&S Earnings	-192	-89	323	-4,911	-4,022	-2,563
ΔTotal Earnings	578	948	1,160	-1,675	-1,765	-1,312
W&S Exiter	.0688	.0761	.0880	.1267	.1047	.0842
Gross Receipts 4853	42,560	43,950	40,890	26,220	22,850	19,080
Net Receipts 4853	12,590	12,980	11,790	8,797	7,647	6,031
Net Receipts non-4853	406	536	844	691	1,218	1,641
W&S Earnings				3,7	-,	-,
Total Earnings	12,990	13,520	12,640	9,488	8,865	7,672
ΔGross Receipts 4853	14,060	16,270	15,200	26,220	22,850	19,080
ΔNet Receipts 4853	4,561	5,326	4,991	8,797	7,647	6,031
ΔNet Receipts non-4853	-36	114	361	-629	-335	-95
ΔW&S Earnings	-7,072	-7,938	-8,983	-11,640	-13,400	-14,030
ΔTotal Earnings	-2,547	-2,498	-3,631	-3,477	-6,083	-8,094
W&S Entrant	.0418	.0437	.0517	.0625	.0619	.0598
Gross Receipts 4853	28,060	29,350	27,520	15,870	12,720	9,940
Net Receipts 4853	8,784	9,140	8,009	5,547	4,212	3,008
Net Receipts non-4853	423	506	626	603	1,177	1,300
W&S Earnings	7,826	7,998	8,807	7,234	8,517	9,559
Total Earnings	17,030	17,640	17,440	13,380	13,910	13,870
ΔGross Receipts 4853	-7,180	-7,163	-7,422	15,870	12,720	9,940
ΔNet Receipts 4853	-3,085	-2,991	-3,305	5,547	4,212	3,008
ΔNet Receipts non-4853	-133	-173	-256	-1,998	-1,726	-1,875
ΔW&S Earnings	7,826	7,998	8,807	7,234	8,517	9,559
ΔTotal Earnings	4,608	4,834	5,246	10,780	11,000	10,690
No W&S	.7545	.7257	.6365	.3527	.2516	.1894
Gross Receipts 4853	45,460	46,100	44,920	28,730	25,490	19,130
Net Receipts 4853	13,580	13,580	13,180	9,105	7,921	5,667
Net Receipts non-4853	459	503	660	1,293	2,090	2,810
W&S Earnings				-,-,-	_, , , ,	_,-,
Total Earnings	14,040	14,080	13,840	10,400	10,010	8,477
ΔGross Receipts 4853	1,498	1,220	82	28,730	25,490	19,130
ΔNet Receipts 4853	219	187	4	9,105	7,921	5,667
ΔNet Receipts non-4853	15	21	64	-1,982	-1,745	-1,583
ΔW&S Earnings				1,702	2,7 10	1,000
ΔTotal Earnings	234	208	68	7,122	6,176	4,084
Sample Size (Thousands)	139	153	191	58	110	246
Total Farnings is defined as Net Re						240

Total Earnings is defined as Net Receipts 4853 plus Net Receipts non-4853 plus W&S Earnings.

Table 4b: Descriptive Statistics
Sample: Nonemployers NOT in NAICS 4853: Taxi and Limousine Services

		Incumbents			Entrants	
	2013	2014	2015	2013	2014	2015
W&S Stayer	.3733	.3767	.3814	.5685	.5823	.6058
Gross Receipts	23,070	23,080	23,210	12,810	13,250	13,040
Net Receipts	11,210	11,170	11,150	5,788	6,083	5,831
W&S Earnings	51,620	51,590	52,710	40,380	41,270	42,360
Total Earnings	62,830	62,760	63,860	46,170	47,350	48,190
ΔGross Receipts	770	1,026	990	12,810	13,250	13,040
ΔNet Receipts	302	544	484	5,788	6,083	5,831
ΔW&S Earnings	695	1,051	1,603	-4,246	-3,881	-3,560
ΔTotal Earnings	996	1,594	2,087	1,542	2,201	2,271
W&S Exiter	.0609	.0615	.0617	.0891	.0865	.0850
Gross Receipts	42,640	43,530	44,030	21,840	23,220	23,300
Net Receipts	24,600	25,050	25,360	12,860	13,630	13,680
W&S Earnings						
Total Earnings	24,600	25,050	25,360	12,860	13,630	13,680
ΔGross Receipts	12,620	13,740	13,720	21,840	23,220	23,300
ΔNet Receipts	8,216	8,994	9,107	12,860	13,630	13,680
ΔW&S Earnings	-13,680	-14,100	-14,340	-17,970	-18,660	-19,220
ΔTotal Earnings	-5,462	-5,107	-5,229	-5,112	-5,030	-5,536
W&S Entrant	.0553	.0549	.0541	.0720	.0686	.0660
Gross Receipts	27,100	27,100	27,680	13,670	14,350	14,110
Net Receipts	14,960	15,040	15,330	7,599	8,014	7,804
W&S Earnings	12,820	12,770	13,200	9,585	9,885	10,320
Total Earnings	27,770	27,810	28,540	17,180	17,900	18,130
ΔGross Receipts						
ΔNet Receipts	-6,813	-6,495	-6,825	7,599	8,014	7,804
ΔW&S Earnings	12,820	12,770	13,200	9,585	9,885	10,320
ΔTotal Earnings	6,003	6,275	6,377	17,180	17,900	18,130
No W&S	.5105	.5068	.5029	.2704	.2626	.2432
Gross Receipts	51,880	52,520	53,200	30,440	34,740	33,740
Net Receipts	29,590	29,870	30,370	16,640	19,040	18,390
W&S Earnings						
Total Earnings	29,590	29,870	30,370	16,640	19,040	18,390
ΔGross Receipts	833	1,008	604	30,440	34,740	33,740
ΔNet Receipts	301	525	481	16,640	19,040	18,390
ΔW&S Earnings						
ΔTotal Earnings	301	525	481	16,640	19,040	18,390
Sample Size (Thousands)	12,850	13,090	13,440	5,664	5,973	5,820

Total Earnings is defined as Net Receipts plus W&S Earnings.

Table 5a: OLS Regressions, Dependent variable = Annual Earnings Growth Sample: Nonemployers in NAICS 4853: Taxi and Limousine Services

	(2)	(3)	(4)	(5)
		025	008	013
-1,312	208	183	210	202
	241	216	268	259
-1,675	336	310	370	361
1,160	057	032	052	044
948	021	.005	004	.005
578	.005	.031	.035	.044
-8,094	-2.782	-2.756	-2.785	-2.777
			-2.007	-1.999
	-1.552	-1.527	-1.602	-1.595
				-1.165
	674	649	714	706
	792	766	828	820
10,690	7.350	7.375	7.293	7.301
				7.352
				7.503
				1.150
	1.048			1.044
	.916	.941	.908	.915
4,084	4.256	4.281	4.315	4.319
				5.389
				5.992
	016	.010	.014	.016
208	.006	.031	.032	.033
234	025			
			.057	.057
			1.510	1.505
			.394	.392
				.105
				065
				159
				419
				.245
				002
			.093	.085
				.035
				023
				002
				.066
		.1923	.1943	.1943
	1,160 948 578 -8,094 -6,083 -3,477 -3,631 -2,498 -2,547 10,690 11,000 10,780 5,246 4,834 4,608 4,084 6,176 7,122 68 208	-1,765	-1,312	-1,312

Notes: Dependent variable in column 1 is year-to-year growth in real total earnings. Dependent variable in columns 2-5 is year-to-year growth in IHS(real total earnings), where IHS(x)=ln{x+sqrt[1+(x\*x)]}. Mean of dependent variable in column 1 is 310. Mean of dependent variable in columns 2-5 is .5437. Sample size is 897,000.

Shaded coefficients are statistically different from zero at the 1% level of significance. Demographic variables in columns 4-5 are entered as deviations from means.

Table 5b: OLS Regressions, Dependent variable = Annual Earnings Growth Sample: Nonemployers NOT in NAICS 4853: Taxi and Limousine Services

	(1)	(2)	(3)	(4)	(5)
Intercept			036	.045	.044
1 if Stayer W&S					
1 if 2015 * Entrant 4853	2,271	071	035	217	215
1 if 2014 * Entrant 4853	2,201	065	029	208	206
1 if 2013 * Entrant 4853	1,542	087	051	230	228
1 if 2015 * Incumbent 4853	2,087	.036	.072	017	015
1 if 2014 * Incumbent 4853	1,594	.035	.071	018	016
1 if 2013 * Incumbent 4853	996	.025	.061	026	024
1 if Exiter W&S					
1 if 2015 * Entrant 4853	-5,536	-1.997	-1.961	-2.133	-2.132
1 if 2014 * Entrant 4853	-5,030	-1.966	-1.931	-2.102	-2.101
1 if 2013 * Entrant 4853	-5,112	-2.016	-1.980	-2.155	-2.154
1 if 2015 * Incumbent 4853	-5,229	-1.247	-1.211	-1.323	-1.322
1 if 2014 * Incumbent 4853	-5,107	-1.243	-1.207	-1.319	-1.318
1 if 2013 * Incumbent 4853	-5,462	-1.283	-1.248	-1.359	-1.359
1 if Entrant W&S					
1 if 2015 * Entrant 4853	18,130	9.406	9.442	9.173	9.173
1 if 2014 * Entrant 4853	17,900	9.410	9.445	9.176	9.176
1 if 2013 * Entrant 4853	17,180	9.359	9.395	9.120	9.120
1 if 2015 * Incumbent 4853	6,377	1.275	1.310	1.166	1.166
1 if 2014 * Incumbent 4853	6,275	1.299	1.335	1.187	1.187
1 if 2013 * Incumbent 4853	6,003	1.317	1.353	1.207	1.207
1 if No W&S					
1 if 2015 * Entrant 4853	18,390	6.771	6.807	6.739	6.739
1 if 2014 * Entrant 4853	19,040	6.963	6.998	6.924	6.924
1 if 2013 * Entrant 4853	16,640	6.855	6.891	6.800	6.800
1 if 2015 * Incumbent 4853	481	038	002	.008	.008
1 if 2014 * Incumbent 4853	525	012	.024	.028	.028
1 if 2013 * Incumbent 4853	301	036			
1 if Female				046	045
1 if Age 14-20				.492	.492
1 if Age 21-24				.412	.409
1 if Age 25-34				.134	.130
1 if Age 45-54				073	072
1 if Age 55-64				220	219
1 if Age 65-99				544	543
1 if Foreign Born				.160	.156
1 if Nonwhite				028	030
1 if Hispanic				.061	.049
1 if Education 10					.037
1 if Education 14					017
1 if Education 16					013
1 if Education Missing					008
R-Squared			.2440	,2465	.2465
Notes: Dependent variable in column 1	:		4-4-1	Danandanta	anialala in

Notes: Dependent variable in column 1 is year-to-year growth in real total earnings. Dependent variable in columns 2-5 is year-to-year growth in IHS(real total earnings), where IHS(x)=ln{x+sqrt[1+(x\*x)]}. Mean of dependent variable in column 1 is 2606. Mean of dependent variable in columns 2-5 is .6718. Sample size is 56,830,000.

Shaded coefficients are statistically different from zero at the 1% level of significance.

Demographic variables in columns 4-5 are entered as deviations from means.

Table 6a: OLS Regressions, Dependent variable = 1 if Remain Nonemployer 4853 Next Year Sample: Nonemployers in NAICS 4853: Taxi and Limousine Services who were not Nonemployers in NAICS 4853 two years earlier

	(1)	(2)	(3)	(4)	(5)
Intercept		.6580	.6477	.6477	.6364
Year 2012	.6580				
Year 2014	.6078	0502	0345	0345	0172
1 if Female			1527	1527	1480
1 if Age 14-20			1584	1628	1682
1 if Age 21-24			0716	0727	0689
1 if Age 25-34			0339	0339	0292
1 if Age 35-44					
1 if Age 45-54			.0092	.0089	.0026
1 if Age 55-64			.0199	.0181	.0050
1 if Age 65-99			.0284	.0241	0010
1 if Foreign Born			.1932	.1919	.1751
1 if Nonwhite			.0126	.0127	.0144
1 if Hispanic			0491	0458	0498
1 if Education 10				0077	0116
1 if Education 12					
1 if Education 14				.0047	.0066
1 if Education 16				.0097	.0125
1 if Education Missing				.0479	.0034
IHS Net Receipts 4853					.0031
{0,1} LEHD Earnings					0937
R-Squared		.0024	.0671	.0675	.0795

Notes: Mean of dependent variable is .6251. Sample size is 212,000.

Shaded coefficients are statistically different from zero at the 1% level of significance.

Demographic and earnings variables in columns 3-5 are entered as deviations from means.

Table 6b: OLS Regressions, Dependent variable = 1 if Remain Nonemployer Next Year Sample: Nonemployers NOT in NAICS 4853: Taxi and Limousine Services who were not Nonemployers two years earlier

	1 /15	l (2)	l (2)		l (5)
	(1)	(2)	(3)	(4)	(5)
Intercept		.5573	.5568	.5568	.5554
Year 2013	.5573				
Year 2014	.5609	.0036	.0044	.0045	.0073
1 if Female			.0187	.0184	.0150
1 if Age 14-20			1264	1300	1350
1 if Age 21-24			0991	0987	0935
1 if Age 25-34			0311	0299	0263
1 if Age 35-44					
1 if Age 45-54			.0054	.0045	.0021
1 if Age 55-64			.0153	.0122	.0011
1 if Age 65-99			.0052	0027	0367
1 if Foreign Born			.0328	.0311	.0206
1 if Nonwhite			0615	0602	0549
1 if Hispanic			0413	0377	0355
1 if Education 10				0023	0068
1 if Education 12					
1 if Education 14				.0035	.0064
1 if Education 16				.0132	.0191
1 if Education Missing				.0877	.0254
IHS Net Receipts 4853					.0020
{0,1} LEHD Earnings					1149
R-Squared		.0000	.0095	.0102	.0237

Notes: Mean of dependent variable is .5591. Sample size is 15,460,000.

Shaded coefficients are statistically different from zero at the 1% level of significance.

Demographic and earnings variables in columns 3-5 are entered as deviations from means.

Table 7a: OLS Regressions, Dependent Variable = 1 if Enter Nonemployer Industry 4853, 0 if no entry (\*100) Mean of Dependent Variable = .0542

	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)	t-stat
1 if Year = $2013$	.3339								
1 if Year = $2014$	.3395	.0193	.0193	.0193	0071	0070	0064	0061	-24.5
1 if Year = 2015	.3267	.0719	.0710	.0711	.0162	.0156	.0164	.0179	49.3
Labor force status last year:									
Wage and salary	.5463		.0307	.0298		.0297	0024	0312	-120.9
Non-4853 NonEmp	.0291		.0699	.0699		.0699	0526	0839	-119.2
Both W&S and NonEmp	.0224		.1776	.1766		.1765	.0118	0292	-35.9
1 if Displaced last year	.0326			.0159		.0160	.0061	.0023	3.5
Years (+1) that Uber has been									
in CBSA, 0 if not in CBSA	1.483				.0418	.0417	.0237	.0242	103.3
Interaction with Years Uber:									
Wage and salary	.8260						.0221	.0218	199.5
Non-4853 NonEmp	.0442						.0812	.0769	246.6
Both W&S and NonEmp	.0363						.1037	.1021	293.4
Displacement * (Years Uber)	.0489						.0063	.0084	28.5
Demographics variables		No	No	No	No	No	No	Yes	
R-Squared		.0002	.0003	.0003	.0002	.0004	.0006	.0016	

<sup>1)</sup> Demographic variables are dummy variables for Gender, Age {14-20, 21-24, 25-34, 45-54, 55-64, 65-99}, Foreign Born, Nonwhite, Hispanic Ethnicity, Education {10, 12, 13-15, 16+}, and indicators for whether demographics are missing.

<sup>2)</sup> All regressions include an indicator for whether Nonemployer data is not matched to RCF.

<sup>3)</sup> All coefficients except the intercept in columns 1-6 are statistically different from zero at the 1% level of significance (two tailed test).

<sup>4)</sup> All regressions are estimated using deviations from CBSA means; there are 919 CBSAs. Means are reported for levels, not deviations.

<sup>5)</sup> Sample is 2013-2015 population at risk for entering nonemployer industry 4853 (industry 4853 incumbents are removed). Sample size is 764,100,000.

Table 7b: OLS Regressions, Dependent Variable = 1 if Enter Nonemployer NOT Industry 4853, 0 if no entry (\*100) Mean of Dependent Variable = 2.411

	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)	t-stat
1 if Year = 2013	.3343								
1 if Year = $2014$	.3401	.0938	.0941	.0943	.0876	.0899	.0905	.1085	65.8
1 if Year = 2015	.3257	.0506	.0292	.0308	.0376	.0215	.0222	.0651	27.0
Labor force Status last year:									
Wage and salary	.5759		1.091	1.072		1.072	1.006	1027	-61.3
1 if Displaced last year	.0329			.3325		.3325	.2003	.2768	64.2
Years (+1) that Uber has been									
in CBSA, 0 if not in CBSA	1.478				.0097	.0070	0233	.0019	1.2
Interaction with Years Uber:									
Wage and salary	.8703						.0454	.0237	33.6
Displacement * (Years Uber)	.0490						.0890	.1117	57.1
Demographics variables		No	No	No	No	No	No	Yes	
R-Squared		.0000	.0013	.0013	.0000	.0013	.0013	.0088	

<sup>1)</sup> Demographic variables are dummy variables for Gender, Age {14-20, 21-24, 25-34, 45-54, 55-64, 65-99}, Foreign Born, Nonwhite, Hispanic Ethnicity, Education {10, 12, 13-15, 16+}, and indicators for whether demographics are missing.

<sup>2)</sup> All regressions include an indicator for whether Nonemployer data is not matched to RCF.

<sup>3)</sup> All coefficients except the intercept in columns 1-6 are statistically different from zero at the 1% level of significance (two tailed test).

<sup>4)</sup> All regressions are estimated using deviations from CBSA means; there are 919 CBSAs. Means are reported for levels, not deviations.

<sup>5)</sup> Sample is 2013-2015 population at risk for entering nonemployer NOT industry 4853 (industry 4853 nonemployers and NOT industry 4853 incumbents are removed). Sample size is 724,300,000.