

**The Effect of Uber's Entrance on Wages
for Low-Skilled Occupations Across the United States**

Devin Sun

Department of Economics, Princeton University

Advised by Adrien Matray

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This paper represents my own work in accordance with University regulations.

A handwritten signature in black ink, appearing to read 'Devin A', with a stylized, cursive script.

1 Introduction

The rise of the gig economy is rooted in the aftermath of the 2008 financial crisis in the United States. Unable to maintain steady employment, Americans sought out additional sources of income to supplement a variety of alternative working arrangements. More than a decade after its conception, the platform economy has now grown substantially and accounts for nearly 15 percent of employment numbers, according to the Bureau of Labor Statistics (BLS). As independent contracting opportunities become more commonplace, the economy that envelops them continues to be driven by a demand for flexible work hours and convenience.

The rise of the sharing economy shows no signs of slowing down, raising questions surrounding the industry's impact on labor markets at both local and national scales. In the latter half of 2019, the U.S. unemployment rate reached a 50-year low of 3.5 percent. The metric is illustrative of the relatively tight labor market that Americans have enjoyed that has persisted along with the longest-running bull market that celebrated its 10-year anniversary in March 2019. With that growth grew the gig economy, which offered key advantages to its employees that ranged from schedule flexibility to employee autonomy. The incentives of partnering with a gig platform afforded employees a bounty of novel opportunities that rivaled those of traditional career paths.

In a tight labor market environment, employers experience constant pressure to compete against other firms in order to attract top talent by leveraging a laundry list of occupational benefits such as higher wages, employee benefits, and workplace convenience. Although there exists much literature on the gig economy and its effects, current empirical analyses primarily focus on the industry's implications for platform

workers and their conventional counterparts within the traditional workforce. This paper specifically aims to explore the effects of the ride-sharing economy on wages for low-skilled occupations in the United States. More specifically, what effect does the introduction of ride-sharing platforms such as Uber have on average wages for workers in occupations that require little to no degree of job preparation? I hypothesize that, all else equal, the unparalleled and unique benefits of schedule flexibility, worker autonomy, and ease of entry that are intrinsic to ride-sharing platforms pressure conventional employers to disproportionately raise wages for workers in low-skilled occupations in tight labor markets.

Secondary to the question is an investigation of the gig economy's spillover effects on employment numbers across different industries and cities. To this, I hypothesize that industries that are most exposed to low-skilled labor will be most negatively impacted as employees move to job opportunities with gig platforms. I draw upon annual American Community Survey (ACS) data to analyze the effect of Uber's entrance into a new city on wages for low-skill and high-skill occupations, as defined by the U.S. Department of Labor. Additionally, I assume that lower-skilled workers, defined as "occupations that need little or no preparation," are those directly affected by the optionality that is introduced when Uber enters a new city. This distinction is crucial to differentiating between treatment (low-skilled) and control (skilled) groups within the workforce to conduct a difference-in-differences analysis.

2 Literature Review

Abraham, Haltiwanger, and Sandusky (2019) offer a comprehensive overview on the gig economy. Specifically pinpointing a significant growth of the gig industry

beginning in 2013, Abraham et al. (2019) note a growing discrepancy between Current Population Survey (CPS) data and administrative data; whereas the former does not reflect the platform economy's rapid growth, the latter reveals a marked increase in self-employment rates. This points out a crucial flaw in typical household surveys: that the design of such questionnaires overlooks self-employment arrangements that are supplemental to other modes of employment. Abraham et al. (2019) allude to several other studies that examine data from private sector sources as a more accurate reflection of gig economy growth. BLS data, for example, reflects a growth of 298% in Ground Passenger Transportation employees between 2010 and 2016. A relative new innovation within the past decade, the gig economy is gaining traction at a quickening pace and therefore invites opportunities for study.

Drawing upon a sample of workers on the Amazon Mechanical Turk platform, an online outsourcing marketplace, Doucette and Bradford (2019) explore the motivations for workers in the process of allocating time between gig and primary jobs. Most significantly, men and women, Doucette and Bradford (2019) find, report different reasons for participating in the gig economy. Specifically, men reported spending more time on gig jobs to increase their incomes, whereas women spent more time on gig jobs to combat insecurities from their primary occupations. The authors point out that the gig economy is enticing because it facilitates the process of matching workers with appropriate tasks in relation to individuals' preferences for hours or natures of work. Being able to match each aspect of a worker's "profile" encourages more productivity because it allows them to pursue the most efficient allocation of their resources, and therefore promotes efficiency for workers.

Koustas (2019) draws from big data on financial accounts to examine the economic activities of gig economy workers. The dataset describes transactions from a large financial aggregator and bill-paying application. Koustas (2019) compiles a list of companies that participate in the gig economy, excluding companies that require specialized knowledge, focusing instead on platforms that offer common services. Of the entire dataset, approximately 25,000 earners on 10 popular gig platforms satisfied their criteria, with Uber and Lyft accounting for nearly 90 percent of the sample; his findings therefore show the entrenched market segmentation of the gig economy. The prevalence of Uber and Lyft allow me to narrow my empirical analysis of the gig economy to ride-sharing companies as a representative sample for our effect.

Barzilay and Ben-David (2017) supplement the existing literature by providing a study on the demographics of the gig economy's participants, primarily focusing on gender inequality. Named a new period of sex inequality, "Discrimination 3.0" is characterized by their finding from a platform's dataset that women's hourly wages are on average two-thirds those of men, despite women working longer hours than men on gig platforms. Although such platforms allow laborers more anonymity and impartiality, there also exist many pitfalls. With many platforms classifying their employees as independent contractors, they are able to circumvent regulations that require benefits such as overtime pay, minimum wage, and family leave. Furthermore, under a supply-and-demand framework, the accessibility of labor supply on gig platforms introduces the possibility for bidding wars that would effectively lower workers' net wages.

Cook, Diamond, and Oyer (2019) conduct a cross-dimensional study of the relationship between the age of Uber driver-partners and their average hourly earnings. Using data from the March Current Population Survey, Cook et al. (2019) find that

average earnings for workers increase steadily for about 20 years from the moment they enter the workforce, and then stagnate for the remainder of their careers. These findings contrast with an analysis of proprietary data from Uber that suggests another narrative. Specifically, hourly earnings for Uber drivers are unrelated to age for drivers in their 20s and 30s, but then fall rapidly and steadily for drivers older than 40. Cook et al. (2019) conclude that younger Uber driver-partners have an inherent advantage over older workers in terms of hourly earnings.

Berger, Chen, and Frey (2018) explore the impact of Uber on the earnings and employment of traditional taxi drivers in the United States. Using data from Metropolitan Statistical Areas (MSAs) and an analysis on incumbent drivers from ACS samples, Berger et al. (2018) conclude that Uber's entry into a new geography results in a 10-percent earnings decline for incumbent drivers. They offer two possible explanations: (1) that Uber decreased demand for conventional taxi rides, thereby reducing their earnings; and (2) that the most productive drivers exited the taxi industry to become Uber driver-partners. Their methodology includes a triple-differences design that compares earnings among taxi drivers relative to bus and truck drivers working within the same MSA. I draw upon Berger et al. (2018) and their differences design to determine the effect of Uber's presence on earnings across multiple populations.

Etzioni (2018) discusses the importance of the lack of benefits faced by gig economy workers. As many other authors note, independent contractors are unable to take advantage of benefits that are available to traditional employees such as insurance, paid and unpaid leave, and retirement contributions. Specifically, gig economy workers do not receive benefits and are not guaranteed a minimum wage, therefore they find themselves vulnerable to the possibility of stunted earnings over time compared to their

traditional worker counterparts. However, Etzioni (2018) looks to a changing tide in policy, citing a policy change in California that requires gig economy companies to treat their workers as traditional employees that entitles them to the same protections as conventional workers.

Finally, Hall and Krueger (2016) provide the first comprehensive analysis of Uber's driver-partners. The Chief Economist at Uber and a Princeton economist, Jonathan Hall and Alan Krueger conduct a comprehensive analysis of Uber's driver-partners based on anonymized administrative data from Uber, two external surveys conducted by Benenson Strategy Group (BSG), and government surveys of taxi drivers and chauffeurs. Their study emphasizes several key findings. First, drivers choose to partner with Uber because of flexible scheduling, competitive compensation, relatively stable hourly earnings. Second, the age and education characteristics of Uber's driver-partners mirror those of the general workforce more than they do to taxi drivers and chauffeurs. And third, a direct comparison of net hourly earnings of Uber's driver-partners to those of taxi drivers is ultimately difficult in practice, but it would appear that Uber drivers earn at least as much as taxi drivers and chauffeurs.

3 Data

For my difference-in-differences analysis, I collect data on which cities have been exposed to the treatment and when. Using a combination of Uber's website and various local news outlets, I compile a list of cities in which Uber is present and the months and years in which the service launched for those given cities. This list is then cross-referenced with the list of cities that are comprehensively represented in the American Community Survey dataset. The product of this process is a list of cities from which I am able to study

the effect of Uber’s entrance over an extended time period. The list is then further specified to describe cities that are also described within the BLS dataset for my employment analysis.

3.1 Wage Data

To construct a model that reflects the effect of Uber’s entrance on wages for low-skilled workers, the study calls for data on treatment and control groups, for which I characterize as low-skilled and high-skilled workers, respectively. The entrance of Uber into a city represents the event shock that primarily affects the treated group. I draw upon several datasets that inform the model.

From ACS data, I extract several variables that are critical to my study: (1) total wages, (2) occupation, (3) city, and (4) survey year. My primary period of interest is the most recent decade of available information, representing the annual ACS samples from 2008 to 2017. Additionally, as my difference-in-differences analysis occurs over a period of time, I adjust the ACS data figures for wages to represent their real values, instead of the nominal values collected in the data. The ACS dataset offers a CPI multiplier for each year that uses 1999 as the base year, which I am able to use to convert nominal wages to real wages. Table 1 summarizes several key metrics for each of the variables.

Table 1: Summary Statistics for ACS Data

| VARIABLES | (1) N | (2) Min | (3) Max | (5) Mean | (6) SD | (7) P50 |
|-----------------------------------|----------|------------|------------|-------------|-----------|------------|
| Yearly Mean Wage, base = 1999 | 57,090 | 0 | 459,558 | 26,552 | 24,010 | 24,010 |
| Log Yearly Mean Wage, base = 1999 | 57,090 | 0 | 13.04 | 9.408 | 2.304 | 2.304 |
| Job Zone | 57,090 | 1 | 5 | 2.924 | 1.046 | 1.046 |
| Census Year | 57,090 | 2008 | 2017 | | | |
| Uber Entry Year | 57,090 | 2011 | 2016 | | | |
| City | 57,090 | 1 | 31 | | | |

Another key component of the study is the criteria upon which low- and high-skilled occupations are defined and categorized. I draw upon the U.S. Department of Labor’s O*NET database, which offers detailed descriptions for a variety of professions and are stored in the *Job Zone* variable. Among many metrics, the Department of Labor has outlined and assigned job zones, which they define to be groups of “occupations that are similar in: how much education people need to work; how much related experience people need to do the work; and how much on-the-job training people need to do the work.” The database outlines five distinct job zones, which are denoted in Table 2.

Table 2: U.S. Department of Labor O*NET Job Zones and Descriptions

| | |
|---|--|
| 1 | Occupations that need little or no preparation |
| 2 | Occupations that need some preparation |
| 3 | Occupations that need medium preparation |
| 4 | Occupations that need medium preparation |
| 5 | Occupations that need extensive preparation |

The O*NET database uses the Standard Occupational Classification (SOC) System, which uses a series of 6 digits to categorize professions. The ACS dataset offers occupations for each observation coded using the SOC System. Furthermore, the occupations relevant to the dataset and their respective job zones are given in Appendix A.

3.2 Employment Data

My secondary analysis of Uber’s entrance into a city on employment across different industries calls for employment data. It is therefore important to retrieve employment numbers over the time period relevant to the study. The Bureau of Labor Statistics offers such data broken down into month and year, detailing 11 specific industries for various cities. Table 3 describes summary statistics for the dataset.

Table 3: Summary Statistics for BLS Data

| VARIABLES | (1) N | (2) Min | (3) Max | (5) Mean | (6) SD | (7) P50 |
|-------------------------------|----------|------------|------------|-------------|-----------|------------|
| Industry Low-Skill Percentage | 2,970 | 0 | 0.500 | 0.0311 | 0.0481 | 0.0481 |
| Log of Mean Yearly Employees | 2,760 | 5.704 | 13.78 | 11.06 | 1.361 | 1.361 |
| Yearly Mean Employees | 2,760 | 300 | 961,900 | 128,250 | 152,792 | 152,792 |
| Uber Present | 2,760 | 0 | 1 | 0.478 | 0.500 | 0.500 |
| Year | 2,970 | 2008 | 2017 | | | |
| Industry | 2,970 | 1 | 11 | | | |
| MSA (BLS) Name | 2,970 | 1 | 27 | | | |

To remain consistent, I specify my study to cities that have already been used in the analysis on wages. The BLS dataset presents employment numbers at individual industry level across metropolitan state areas (MSAs), which depict geographical regions with relatively high population densities and high degrees of economic and social integration. The industries outlined in the BLS data are listed in Table 4.

Table 4: BLS Industries

| | |
|----|--------------------------------------|
| 1 | Other Services |
| 2 | Financial Activities |
| 3 | Government |
| 4 | Information |
| 5 | Leisure and Hospitality |
| 6 | Manufacturing |
| 7 | Mining and Logging |
| 8 | Education and Health Services |
| 9 | Professional and Business Services |
| 10 | Retail Trade |
| 11 | Trade, Transportation, and Utilities |

4 Methodology

4.1 Wages

The ACS data is first cleaned to generate and isolate for the observations that are relevant and pertinent to my study. For example, Uber was founded in 2008, so all observations in the data prior to 2008 are dropped from the dataset. Additionally, not all geographies in the dataset are available for study. First, I compile a list of cities in which Uber is present and a list of cities that are represented in the ACS data for the period between 2008 and 2017. Cross-referencing the two lists for overlap result in 31 cities on which empirical analysis may be conducted. The given cities and their codes are described in Appendix B. Given the 31 cities for study, I drop all observations in the ACS data that are not one of the 31. Using Uber’s website and various local news outlets, I am then able to pinpoint the month and year of Uber’s launch in each one of the 31 cities.

I first seek to answer the definitive question: what is the effect of Uber’s entrance into a city on general average wages? From the ACS dataset, I drop observations with a job zone of 5 because those occupations are highly specific and unrepresentative, and therefore they are deemed outliers with respect to this specific study. After cleaning and isolating for the relevant ACS observations, I regress the natural logarithm of the mean wage for each panel observation on a dummy variable that represents whether or not Uber is present in that city and year. The same regression is also run with 2 configurations of fixed effects: city, and city and year. To ensure that I am able to isolate for the event shock, I restrict the regression to observations within two years before and after the event shock. Furthermore, the variance-covariance is clustered at a city level, which allows for a more precise standard error because the effects are likely to be more similar within individual cities.

$$LNWAGE_{ct} = \beta_1 Uber_Present_{ct} + \varepsilon_{ct} \quad (1)$$

$$LNWAGE_{ct} = \beta_1 Uber_Present_{ct} + \delta_c + \varepsilon_{ct} \quad (2)$$

$$LNWAGE_{ct} = \beta_1 Uber_Present_{ct} + \delta_c + \delta_t + \varepsilon_{ct} \quad (3)$$

I account for several variables: $Uber_Present_{ct}$, which is equal to one if Uber is present in that city in that year and zero if it is not; δ_c , which represents fixed effects for differences across cities; and δ_t , which represents fixed effects for differences across time such as trends in wage growth. I focus my attention on β_1 , which represents the percentage change in average overall wages once Uber enters a city.

Next, I further specify my study to its hypothesis, and so I define low-skilled occupations to be characterized as those with a job zone of 1. Consequently, all occupations with job zones greater than 1 are considered to be high-skilled occupations. Similar to the methodology in addressing the definitive regression, I drop all redundant and irrelevant occupations and those with job zones of 5. With this data, I construct a model to regress the natural logarithm of the mean wage for occupations on a city-year level on several variables representing the event shock, the treatment and control groups, and the interaction of the event shock on the two groups. The interaction of the two dummy variables represents the difference-in-differences estimator. In addition, I cluster the variance-covariance estimator using a variable that groups the skill and year variables, allowing for a more precise standard error because the effects are likely to be more similar within low-skilled and high-skilled occupations.

$$LNWAGE_{oct} = \beta_1 Uber_Present_{ct} + \beta_2 (Uber_Present_{ct} \times Low_Skill_o) + \delta_{Low_Skill,t} + \varepsilon_{oct} \quad (4)$$

$$LNWAGE_{oct} = \beta_1 Uber_Present_{ct} + \beta_2 (Uber_Present_{ct} \times Low_Skill_o) + \delta_{Low_Skill,t} + \delta_c + \varepsilon_{oct} \quad (5)$$

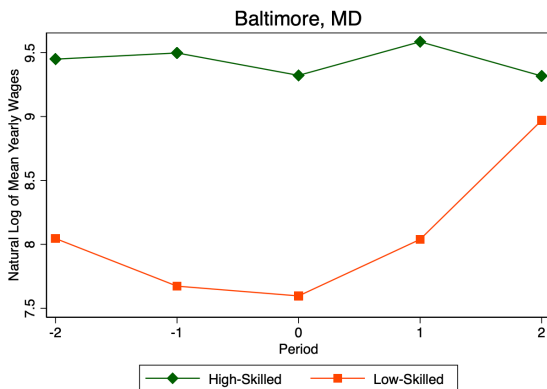
$$LNWAGE_{oct} = \beta_2(Uber_Present_{ct} \times Low_Skill_o) + \delta_{c,t} + \delta_{Low_Skill,t} + \varepsilon_{oct} \quad (6)$$

I account for several variables: $Uber_Present_{ct}$, which is a dummy variable with the value zero if Uber is not yet present in a city and one if it is present; Low_Skill_o , which is a dummy variable with the value zero if the occupation is high-skilled and one if it is low-skilled; $(Uber_Present_{ct} \times Low_Skill_o)$, which is the interaction between $Uber_Present_{ct}$ and Low_Skill_o ; δ_c , which represents the city-level fixed effects that account for differences across cities; $\delta_{c,t}$, which represents the city-by-year fixed effects that account for different characteristics across cities and time; and $\delta_{Low_Skill,t}$, which represents the skill-by-year fixed effects that account for wage trends among low-skilled and high-skilled occupations over time. I focus my attention on β_2 because it indicates the marginal effect of Uber's presence in a city on wages for low-skilled occupations relative to wages for their high-skilled counterparts. I also supplement my study with β_1 in regressions (4) and (5) to understand the effect that Uber's effect has on wages for high-skilled occupations. I run this regression for all cities in the sample.

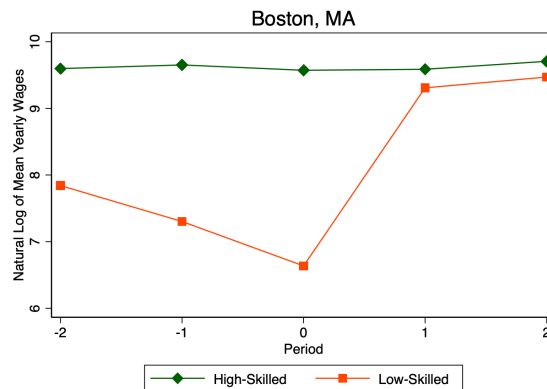
I further bolster the validity of my methodology by considering that difference-in-differences analyses must follow three core assumptions: (1) that intervention is unrelated to outcome at baseline; (2) the observation on one individual should be unaffected by the particular assignment of treatments to the other units; and (3) the treatment and control groups have parallel trends in outcome. First, I assume that the decision for Uber to enter a city is generally motivated by profit, and is otherwise nondiscriminatory in their product's rollout. Second, the effect of the event shock on low-skilled occupations in one city does not affect the observation of the shock on similar

occupations in another city. And third, although perfectly parallel trends in reality are rare, Graph 1 shows that, prior to treatment ($t = 0$), the trends of the natural logarithm of mean wages for low- and high-skilled workers across cities roughly hold. Graphs 1, 2, 3, and 4 display the trends in wages from $t = -2$ to $t = 2$ for the following cities: Baltimore, MD; Boston, MA; Los Angeles, CA; and Philadelphia, PA.

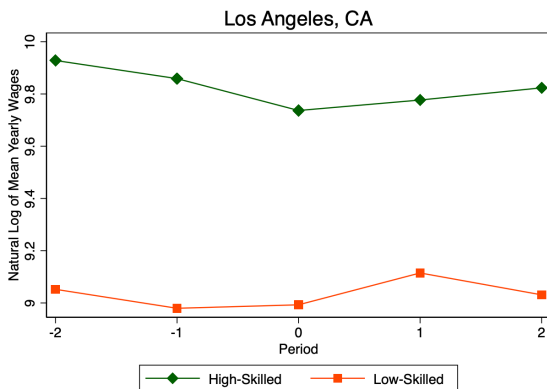
Graph 1: Baltimore, MD



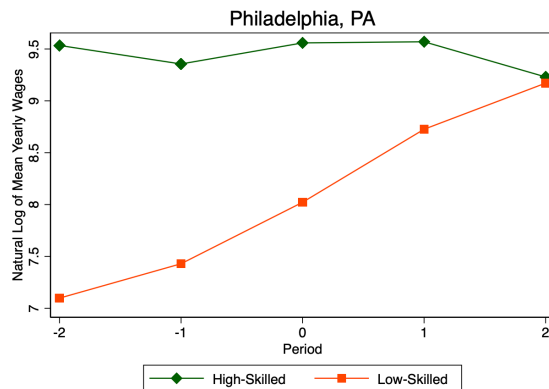
Graph 2: Boston, MA



Graph 3: Los Angeles, CA



Graph 4: Philadelphia, PA



4.2 Employment

The BLS data is cleaned to isolate for the observations that are relevant to this study. Similarly to the cleaning process of the ACS data, all observations in the BLS data

prior to 2008 are dropped from the dataset. Using a list of cities covered in the dataset, I note that four cities represented in the ACS dataset are not available in the BLS dataset: Bridgeport, CT; Manchester, NH; Milwaukee, WI; and Providence, RI. The other 27 cities are represented in the dataset and are listed in Appendix C. The appropriate years of Uber entry for each city are then appended to their respective MSAs.

From the BLS dataset, I primarily require the mean yearly employment figures for each industry in each MSA. These numbers are then combined with the ACS dataset using a many-to-one merge method that appends the appropriate employment numbers to each observation in the ACS depending on that observation's city and industry. This allows me to create panel data on each industry-city-year level that introduces a new variable, *Frac_LowSkill*, that describes the percentage of each industry-city-year observation that is composed of low-skilled occupations.

I then construct a model that regresses the natural logarithm of employment for each industry in each MSA on dummy variables for whether Uber is present or not and the interaction of Uber's presence and the fraction of an industry within a city that is considered low-skilled. The following models are run twice: once, over the entirety of the dataset; and the second time, over a restricted dataset that only includes observations that have non-zero values for *Frac_LowSkill*. The first set of regressions over the entire dataset allows the model to use industries in cities that have no exposure to low-skilled occupations as a pure control group for the difference-in-differences analysis. The second set of regressions run on the restricted dataset only explores the effects on employment for industries that are to a non-zero extent exposed to low-skilled occupations. I expect that models in the latter will result in more extreme regression coefficients than those of the former.

$$\begin{aligned}
LN_EMPLOY_{ict} &= \beta_1 Uber_Present_{ct} \\
&+ \beta_2 (Uber_Present_{ct} \times Frac_LowSkill_{ict}) + \delta_i + \varepsilon_{ict}
\end{aligned} \tag{7}$$

$$\begin{aligned}
LN_EMPLOY_{ict} &= \beta_1 Uber_Present_{ct} \\
&+ \beta_2 (Uber_Present_{ct} \times Frac_LowSkill_{ict}) + \delta_{i,t} + \delta_c \\
&+ \varepsilon_{ict}
\end{aligned} \tag{8}$$

$$\begin{aligned}
LN_EMPLOY_{ict} &= \beta_1 Uber_Present_{ct} \\
&+ \beta_2 (Uber_Present_{ct} \times Frac_LowSkill_{ict}) + \delta_{i,t} + \delta_{c,t} \\
&+ \varepsilon_{ict}
\end{aligned} \tag{9}$$

I account for several variables: $Uber_Present_{ct}$, a dummy variable that has a value of zero if Uber is not yet present in that city in that year and one if it is; and $(Uber_Present_{ct} \times Frac_LowSkill_{ict})$, which represents an interaction term between $Uber_Present_{ct}$ and $Frac_LowSkill_{ict}$, a continuous variable that is calculated as the percentage of a observations in each industry within a city that has been classified as low-skilled occupations. $Frac_LowSkill_{ict}$ serves as a proxy for an industry's exposure to low-skilled labor. I focus my attention on β_2 because it represents the marginal effect on employment of Uber's entrance into a city on different industries. In addition, the variance-covariance estimator is clustered at a year level because observations are likely to be more similar within each year, therefore allowing the regression model to calculate more precise standard errors. I run this regression for the 27 available cities in the dataset.

5 Results and Discussion

5.1 Effects on Wages

The regressions that explore the overarching question are run using (1) no fixed effects, (2) city fixed effects, and (3) city and year fixed effects. The results are shown in

Table 5. Regressions (1) and (2) include a coefficient for $Uber_Present_{ct}$ that is statistically significant at 1% significance levels, for which we find that Uber's entrance into a city is correlated with 9.46% and 9.34% increases in overall mean wages, respectively. Regression (3) results in a coefficient for $Uber_Present_{ct}$ of 2.53% that is not statistically significant even at a 10% significance level. Although regressions (1) and (2) suggest that Uber's entrance into a city have positive effects on average wages, they offer a broad picture that only encompasses the effect on overall wages, inclusive of both low-skilled and high-skilled wages. The research question, however, warrants a more specific analysis of the Uber's entrance into a city on wages for low-skilled workers.

Table 5: Regressions on Overall Mean Wages

| VARIABLES | (1) | (2) | (3) |
|---------------------|-----------------------|-----------------------|--------------------|
| <i>Uber_Present</i> | 0.0946*** (0.0234) | 0.0934*** (0.0235) | 0.0253 (0.0568) |
| City FE | No | Yes | Yes |
| Year FE | No | No | Yes |
| Observations | 26,204 | 26,204 | 26,204 |
| R-squared | 0.000 | 0.019 | 0.019 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The findings regarding the initial question appear to suggest that Uber's entrance into a new geography is correlated with an overall increase in average wages. The (1) OLS and (2) city fixed effects regressions return coefficients for $Uber_Present_{ct}$ that indicate an average 9.40% increase in wages for workers as a result of Uber's entrance into a new city. The (3) city and year fixed effects regression results in a positive coefficient, however, it is not statistically significant even at a 10% significance level. The insignificance of the

$Uber_Present_{ct}$ coefficient in regression (3) is likely caused by the addition of year fixed effects, which picks up variation in the dependent variable that occurs over time that cannot be attributed to $Uber_Present_{ct}$. This means that there are likely other factors that the model must consider in its construction, which leads the paper to the primary question that regards the differing impacts between high- and low-skilled occupations. Regardless, the findings support a general notion that Uber has a positive impact on the overall mean wages of a city relative to their wages before Uber is present.

To further understand the effects of Uber's entrance into a city on low-skilled workers, I conduct a difference-in-differences analysis with fixed effects as outlined in the methodology. The results are shown in Table 6, with a more detailed regression table in Appendix D. I run several regressions: (4) with skill-by-year fixed effects, (5) with city and skill-by-year fixed effects, and (6) with city-by-year and skill-by-year fixed effects. Regression (4) results in a coefficient for the interaction term of 26.7% at a 5% significance level. Regression (5) results in a coefficient for the interaction term of 6.79% at a 10% significance level. And regression (6) results in coefficients for the interaction term of 5.96% at a 5% significance level.

Table 6: Regressions on Mean Wages for Low-Skilled Workers

| VARIABLES | (4) | (5) | (6) |
|-----------------------------------|----------------------|----------------------|-----------------------|
| <i>Uber_Present</i> | 0.361** (0.0128) | 0.0276 (0.0524) | |
| <i>(Uber_Present × Low_Skill)</i> | 0.267** (0.00594) | 0.0679* (0.00959) | 0.0596** (0.00251) |
| Skill-by-Year FE | Yes | Yes | Yes |
| City FE | No | Yes | No |
| City-by-Year FE | No | No | Yes |
| Observations | 26,204 | 26,204 | 26,204 |
| R-squared | 0.016 | 0.029 | 0.033 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

I further specify the research question to focus on the effect Uber's entrance into a city on mean wages for low-skilled occupations as opposed to mean wages for both low-skilled and high-skilled occupations. Presented in Table 6, the findings from the regressions on mean wages for low-skilled workers uniformly suggest that there is a positive net impact on the wages for low-skilled occupations, relative to their high-skilled counterparts.

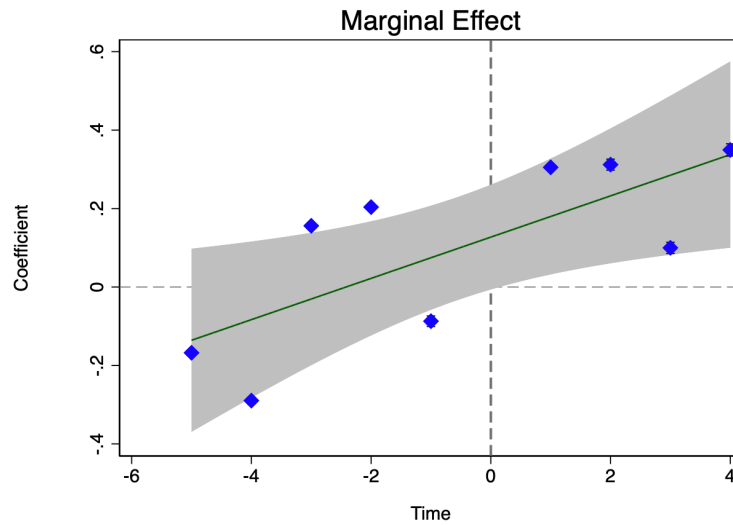
In models (4), (5), and (6), I observe the effects of multiple combinations of fixed effects. When accounting only for skill-by-year fixed effects, the difference-in-differences estimator suggests a 26.7% increase in wages for low-skilled occupations relative to wages for high-skilled occupations. The introduction of skill-by-year fixed effects allows for the consideration of different wage trends between high- and low-skilled occupations over time. I therefore find a salient effect as a result of the event shock in model (4), which

suggests that there is a 26.7% increase in wages for low-skilled occupations as a result of Uber's entrance into a city.

Model (5) accounts for the skill-by-year fixed effects from model (4), but additionally includes variation resulting from differences on the city level. I observe a much lower effect of 6.79% in model (5) because I account for city-level fixed effects in the regression. This discrepancy suggests that Uber enters into cities that generally already have higher wages. Uber's decision to enter more densely populated areas to maximize use of their service is consistent with economic and business principles, as densely populated areas often tend to have higher living costs and thus warrant higher general wages. It therefore makes economic sense for Uber to enter cities that concurrently have generally higher wages.

The final regression in Table 6 displays the results for model (6), which accounts for both city-by-year and skill-by-year fixed effects. Combining the considerations taken in models (4) and (5), the regression suggests that there is a 5.96% increase in wages for low-skilled occupations, relative to wages for high-skilled occupations. This effect is lower than the ones in the OLS and city and skill-by-year fixed effects regressions, which is to be expected because it includes more fixed effects. Regression (6) is likely the most accurate representation of the effects of the event shock on low-skilled occupations because it considers the separate effects on a city-by-year level and across low- and high-skilled occupation. This configuration allows the model to isolate for the effect of Uber's entrance into a geography on low-skilled occupations. Placed in conjunction with findings from the existing body of literature, the results thus appear to support my hypothesis that Uber's entrance into a city causes employers to disproportionately raise wages for workers in low-skilled occupations.

Graph 5: Marginal Effect Coefficients over Time



Graph 5 shows the marginal effects presented by β_2 , or the coefficient on $(Uber_Present \times Low_Skill)$ for the dataset. Evidently, there is an upward trend of the marginal effect on wages for workers in low-skilled occupations when compared to the time of the event shock, or when $t = 0$.

A secondary observation from the regressions presented in Table 6 is the effect that Uber's entrance into a city has on wages for high-skilled occupations. As a result of the *Low_Skill* variable being fixed at zero for all high-skilled observations, the coefficient on only *Uber_Present* gives insight to the effect on wages for high-skilled occupations. The variable only exists in regressions (4) and (5) because of its collinearity with city-by-year fixed effects. Regression (4) shows that there exists a 36.1% increase in wages when considering high-skill observations after Uber enters a new city, and this coefficient is significant at a 5% level. However, when accounting for city fixed effects, I observe that the coefficient for *Uber_Present* is no longer statistically significant. This is likely a result of there being much variation among the observations across different cities with regard to the effect that Uber has on wages for high-skilled occupations. However, the effect

appears to generally describe an increase for workers in high-skilled occupations as well as for those in low-skilled occupations.

5.2 Effects on Employment

I run two sets of regressions, with each on three different models that considers different configurations of fixed effects: first, I run the three models on the entire dataset; and second, I run the three models on a restricted dataset that contains only observations with non-zero values for *Frac_LowSkill*. This allows the study to consider both scenarios. The first set of regressions are detailed in Table 7.

Table 7: Employment Regressions on Unrestricted Dataset

| VARIABLES | (7) | (8) | (9) |
|---|--------------------|-----------------------|--------------------|
| <i>Uber_Present</i> | 0.354** (0.143) | 0.0136** (0.00539) | |
| $(Uber_Present \times Frac_LowSkill)$ | -0.470 (0.348) | -0.389* (0.197) | -0.417* (0.202) |
| Industry FE | Yes | No | No |
| Industry-by-Year FE | No | Yes | Yes |
| City FE | No | Yes | No |
| City-by-Year FE | No | No | Yes |
| Observations | 2,760 | 2,760 | 2,760 |
| R-squared | 0.482 | 0.932 | 0.933 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results appear to suggest that the extent to which an industry is exposed to low-skilled labor is inversely correlated to the effect on its employment numbers as a result of Uber's entrance into a city. The unrestricted dataset allows for the use of industries that, by definition, are purely high-skilled to serve as a control group in my

analytical design. Regression (7) is run using industry fixed effects, allowing the model to differentiate between effects across the 11 industries in the joint ACS-BLS dataset. However, its coefficient of -0.470 is not statistically significant at even a 10% level. Therefore, I look to regressions (8) and (9), which implement different combinations of industry-by-year and city and city-by-year fixed effects.

Regression (8) specifically points to a 38.9% decrease at a 10% significant level in employment for companies that are exposed to low-skilled labor in comparison to their high-skilled counterparts. This regression accounts for industry-by-year and city-level fixed effects, meaning that variation resulting from different industries across time and individual cities that cannot be attributed to the explanatory variables is considered. Likewise, regression (9) provides a similar conclusion because it suggests that industries that are exposed to low-skilled labor experience a 41.7% decrease in employment at a 10% significant level, relative to their high-skilled counterparts. However, regression (9) differs from regression (8) because it factors in city-by-year fixed effects as opposed to only city fixed effects. The substitution of city-by-year fixed effects for simply city fixed effects allows the model to account for variation in the dataset that arises from differences across cities and time. For this reason, regression (9) likely offers a more accurate representation of the Uber's entrance into a city on employment numbers for industries that are exposed to low-skilled labor.

For further study, I also consider the regressions on a restricted dataset that only represents observations with a non-zero value for *Frac_LowSkill*. This is possible because *Frac_LowSkill* is a continuous variable, and so the regressions are calculated on observations that describe industries that are truly exposed to low-skill labor. The

results from regressions (7), (8), and (9) on the restricted dataset are presented in Table 8.

Table 8: Employment Regressions on Restricted Dataset

| VARIABLES | (7) | (8) | (9) |
|---------------------------------------|----------------------|----------------------|-----------------------|
| <i>Uber_Present</i> | 0.443*** (0.105) | 0.0527 (0.0327) | |
| <i>(Uber_Present × Frac_LowSkill)</i> | -2.578*** (0.556) | -0.892*** (0.193) | -0.945*** (0.229) |
| Constant | 11.14*** (0.0629) | 11.29*** (0.0118) | 11.32*** (0.00579) |
| Industry FE | Yes | No | No |
| Industry-by-Year FE | No | Yes | Yes |
| City FE | No | Yes | No |
| City-by-Year FE | No | No | Yes |
| Observations | 1,702 | 1,697 | 1,697 |
| R-squared | 0.491 | 0.942 | 0.946 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

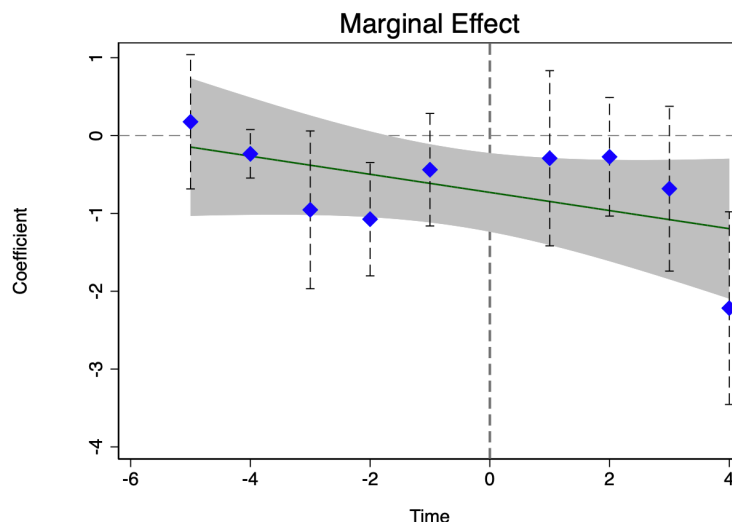
The regressions on the restricted dataset seem to offer a similar conclusion to the one presented by the regressions on the unrestricted dataset: that the degree to which an industry is exposed to low-skilled labor is inversely related to the effect on that industry's employment numbers as a result of Uber's entrance into a new city. However, the coefficients in the regressions on the restricted dataset are more extreme than those for the regressions on the unrestricted dataset. This behavior is expected because it excludes industries that are not exposed to low-skilled labor.

These findings are in line with the initial hypothesis and findings from the regressions on wages. The understanding of the economic phenomenon at work is that,

in a fixed labor supply in a competitive labor market, employees as the producers are given bargaining power when presented with competitive alternatives. Thus, when Uber enters a new city, it offers workers in low-skilled occupations an alternative source of income that may attract low-skilled employees from other industries. As a result of a relatively fixed labor supply, firms operating in other industries must seek ways to retain their employees and prevent them from leaving to become an Uber driver partner. Employers must then offer additional benefits to remain competitive in their demand for workers, and so they must raise wages to make their employees' earnings comparable to those who may seek to drive for Uber.

However, the aforementioned analysis on the effects of Uber's entrance into a city on employment numbers across different industries is indicative of an inability by employers of workers in low-skilled occupations to remain competitive in their offerings. For that reason, I observe from the regressions presented in Tables 7 and 8 that there is a net outflow of employees from industries that are the most exposed to low-skilled labor following the entrance of Uber into a new city. Graph 6 shows results from the unrestricted analysis for the marginal effect on employment for industries exposed to low-skilled occupations over time, relative to the time of the event shock, or when $t = 0$. There appears to be a downward trend in employment figures for industries that are exposed to low-skilled occupations as a result of the entrance of Uber into a new city.

Graph 6: Marginal Effect Coefficients over Time



Paired with the difference-in-differences analysis on wages, one may arrive at a more comprehensive understanding of the changing occupational landscape for low-skilled occupations. It appears that although wages increase more for workers in low-skilled occupations than they do for their high-skilled counterparts, the increase in wages has not been enough to maintain a competitive wage to retain low-skilled employees. Instead, these workers may have opted to drive for Uber as a result of a higher potential for earnings and the platform's convenience and flexibility.

6 Limitations

This study is not without its limitations. First and foremost, the breadth of the data is limiting. Uber itself is available in over 600 cities across 65 countries. Although it would be ideal to study the effects of its entrance into each of the cities in which Uber's services are available, it is difficult to obtain reliable and consistent data that comprehensively covers the company's reach. The data and metrics that are measured—employment and wages—are only available at a sufficient scale from government surveys and organizations

such as the U.S. Census, American Community Survey, or the Bureau of Labor Statistics. Even then, the data collected is skewed, as the surveys tend to overrepresent the most densely populated regions of each state. Because a city cannot necessarily be reduced to a single populous area within the state, the data primarily describe the relevant effects for the economic centers within each city. At the same time, the effects of Uber on wages and employment may be confounded with other factors that drew Uber to launch in that region in the first place.

Additionally, the study does not account for whether other ride-sharing competitors were already present in an area before Uber decided to launch there. More generally, it does not consider the presence of other gig economy platforms that are available in an area before Uber launches there. These two considerations can alter the effects of Uber's presence on metrics because effects of the gig economy may have already been incorporated into the numbers. Similarly, other explanatory variables such as the population of a given city, the introduction of labor legislation, and state-economy makeup are not considered, and thus may introduce omitted variable bias.

Furthermore, the employment analysis utilizes the largest city within each MSA as a representative sample for the entirety of the MSA. The ACS dataset offers data on individual cities, whereas the BLS dataset offers data in terms of MSAs. Although some cities are large and densely populated to such an extent that they have been classified MSAs themselves, many cities are also grouped with several other neighboring cities to define an MSA. This can result in an inconsistency in the employment regressions by misstating the degrees to which certain industries are exposed to low-skilled labor. However, I am confident that this should not significantly alter my final conclusions

because the largest cities addressed in the ACS dataset are likely to represent sufficient samples that may be generalized to their neighboring cities within their MSAs.

This paper also highlights additional areas for future research, most notably in combining proprietary data from Uber with macroeconomic metrics such as employment and wages. The research primarily offers a one-sided narrative that presumes that Uber's benefits are enticing enough by themselves that they have direct, measurable effects in the macroeconomy. The current body of literature seems to support that notion; however, until more research is conducted to understand and isolate for the causal effects of Uber on other metrics, this paper is limited in its ability to deliver the intersection of the two narratives.

7 Conclusion

Ultimately, the gig economy remains a relatively new innovation, and as a result, scholars have yet to understand the full implications of its introduction into cities throughout the United States. Although much of the existing literature focuses on the growing trend of Uber and its effect on direct market participants such as Uber driver-partners and conventional taxi drivers and chauffeurs, this study aimed to analyze the effects of the Uber's presence on macroeconomic metrics such as employment and wages across the United States. As Hall and Krueger (2016) conclude, the demographic makeup of Uber drivers is similar to that of the general workforce, and thus this paper's initial investigation into the effects of Uber's entrance into a city on wages of the workforce as a whole supports that notion.

Understanding that the effects of Uber extend to nearly all workers—regardless of skill level—I use a combination of Uber press releases and ACS data to arrive at a novel

conclusion. My findings appear to support the hypothesis that Uber's entrance into a city is positively correlated with and reasonably leads to an increase in wages of workers in low-skilled occupations, relative to those of workers in high-skilled occupations. Specifically, I run a difference-in-differences analysis by regressing the natural logarithm of mean wages on the interaction between the skill level of an occupation and whether or not Uber is present in the given city. The resulting regression results in a conclusion that benefits workers in low-skilled occupations more than their high-skilled counterparts. With city-by-year and skill-by-year fixed effects, I find that average wages for low-skilled occupations is relatively higher by 5.96% after Uber enters a city.

Additionally, I aimed to analyze the effects of Uber's entrance into a city not only on wages, but also on employment across a number of different industries. Accessing BLS data for employment numbers across 11 specific industries, I find that the effect of Uber's entrance on employment is inversely correlated to the degree to which a given industry is exposed to low-skilled labor. Using two sets of datasets—one restricted and one unrestricted—I arrive at the same conclusion regardless, that employment numbers in industries that are most exposed to low-skilled labor are negatively impacted. This represents the spillover effects that occur simultaneously with the increase in wages of low-skilled occupations that I observed.

The findings from this paper thus support my hypothesis that Uber is positively correlated with a net increase in wages for low-skilled occupations, especially in a tight labor market. Noted in existing literature, the attractive benefits that ride-sharing platforms afford their employees—schedule flexibility, worker autonomy, and ease of entrance, to name a few—ultimately apply an upward pressure on low-skilled wages because firms are forced to remain competitive in a tight labor market with a fixed supply.

Synthesizing the findings from my difference-in-differences analyses conducted on wage and employment data from the American Community Survey and Bureau of Labor Statistics, it is evident that employers who are reliant on low-skilled occupations have largely been unable to remain competitive in a labor market characterized by a relatively fixed supply. Instead, employees in low-skilled occupations have been able to leverage their bargaining power and are thus attracted by more lucrative opportunities offered by Uber.

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Appendix A: SOC Occupation Codes

| SOC Code | Occupation Title | Job Zone |
|-----------------|--|-----------------|
| 352010 | Cooks | 1 |
| 352021 | Food Preparation Workers | 1 |
| 353021 | Combined Food Preparation and Serving Workers, Including Fast Food | 1 |
| 353022 | Counter Attendant, Cafeteria, Food Concession, and Coffee Shop | 1 |
| 353041 | Food Servers, Nonrestaurant | 1 |
| 359021 | Dishwashers | 1 |
| 373010 | Grounds Maintenance Workers | 1 |
| 393090 | Miscellaneous Entertainment Attendants and Related Workers | 1 |
| 419091 | Door-to-Door Sales Workers, News and Street Vendors, and Related Workers | 1 |
| 452041 | Graders and Sorters, Agricultural Products | 1 |
| 454020 | Logging Workers | 1 |
| 472050 | Cement Masons, Concrete Finishers, and Terrazzo Workers | 1 |
| 472161 | Plasterers and Stucco Masons | 1 |
| 4750YY | Derrick, Rotary Drill, and Service Unit Operators, Oil, Gas, and Mining | 1 |
| 516011 | Laundry and Dry-Cleaning Workers | 1 |
| 516021 | Pressers, Textile, Garment, and Related Materials | 1 |
| 516031 | Sewing Machine Operators | 1 |
| 519030 | Cutting Workers | 1 |
| 5360XX | Bridge and Lock Tenders | 1 |
| 119051 | Food Service Managers | 2 |
| 119XXX | Postmasters and Mail Superintendents | 2 |
| 272011 | Actors | 2 |
| 272020 | Athletes, Coaches, Umpires, and Related Workers | 2 |
| 292050 | Health Diagnosing and Treating Practitioner Support Technicians | 2 |
| 311010 | Nursing, Psychiatric, and Home Health Aides | 2 |
| 319095 | Pharmacy Aides | 2 |
| 333010 | Bailiffs, Correctional Officers, and Jailers | 2 |
| 339011 | Animal Control Workers | 2 |
| 339030 | Security Guards and Gaming Surveillance Officers | 2 |
| 339091 | Crossing Guards | 2 |
| 339093 | Transportation Security Screeners | 2 |
| 351012 | First-Line Supervisors of Food Preparation and Serving Workers | 2 |
| 353011 | Bartenders | 2 |
| 353031 | Waiters and Waitresses | 2 |

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|--------|--|---|
| 359031 | Host and Hostesses, Restaurant, Lounge, and Coffee Shop | 2 |
| 371011 | First-Line Supervisors of Housekeeping and Janitorial Workers | 2 |
| 37201X | Janitors and Building Cleaners | 2 |
| 372012 | Maids and Housekeeping Cleaners | 2 |
| 372021 | Pest Control Workers | 2 |
| 391010 | First-Line Supervisors of Gaming Workers | 2 |
| 392011 | Animal Trainers | 2 |
| 392021 | Nonfarm Animal Caretakers | 2 |
| 393010 | Gaming Services Workers | 2 |
| 393021 | Motion Picture Projectionists | 2 |
| 393031 | Ushers, Lobby Attendants, and Ticket Takers | 2 |
| 3940XX | Embalmers and Funeral Attendants | 2 |
| 396010 | Baggage Porters, Bellhops, and Concierges | 2 |
| 399011 | Childcare Workers | 2 |
| 399021 | Personal Care Aides | 2 |
| 411011 | First-Line Supervisors of Retail Sales Workers | 2 |
| 412010 | Cashiers | 2 |
| 412021 | Counter and Rental Clerks | 2 |
| 412022 | Parts Salespersons | 2 |
| 412031 | Retail Salespersons | 2 |
| 419010 | Models, Demonstrators, and Product Promoters | 2 |
| 419041 | Telemarketers | 2 |
| 432011 | Switchboard Operators, Including Answering Service | 2 |
| 432021 | Telephone Operators | 2 |
| 433011 | Bill and Account Collectors | 2 |
| 433021 | Billing and Posting Clerks | 2 |
| 433041 | Gaming Cage Workers | 2 |
| 433051 | Payroll and Timekeeping Clerks | 2 |
| 433071 | Tellers | 2 |
| 434031 | Court, Municipal, and License Clerks | 2 |
| 434051 | Customer Service Representatives | 2 |
| 434071 | File Clerks | 2 |
| 434081 | Hotel, Motel, and Resort Desk Clerks | 2 |
| 434111 | Interviewers, Except Eligibility and Loan | 2 |
| 434121 | Library Assistants, Clerical | 2 |
| 434141 | New Account Clerks | 2 |
| 434XXX | Correspondent clerks and order clerks | 2 |
| 434171 | Receptionists and Information Clerks | 2 |
| 434181 | Reservation and Transportation Ticket Agents and Travel Clerks | 2 |
| 435011 | Cargo and Freight Agents | 2 |
| 435021 | Couriers and Messengers | 2 |
| 435030 | Dispatchers | 2 |

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| 435041 | Meter Readers, Utilities | 2 |
| 435051 | Postal Service Clerks | 2 |
| 435052 | Postal Service Mail Carriers | 2 |
| 435053 | Postal Service Mail Sorters, Processors, and Processing Machine Operators | 2 |
| 435071 | Shipping, Receiving, and Traffic Clerks | 2 |
| 435081 | Stock Clerks and Order Fillers | 2 |
| 435111 | Weighers, Measurers, Checkers, and Samplers, Recordkeeping | 2 |
| 439021 | Data Entry Keyers | 2 |
| 439022 | Word Processors and Typists | 2 |
| 439051 | Mail Clerks and Mail Machine Operators, Except Postal Service | 2 |
| 439061 | Office Clerks, General | 2 |
| 439071 | Office Machine Operators, Except Computer | 2 |
| 451010 | First-Line Supervisors/Managers/Contractors of Farming, Fishing, and Forestry Workers (includes 45-1011 and 45-2031) | 2 |
| 451011 | First-Line Supervisors of farming, fishing, and forestry workers | 2 |
| 452011 | Agricultural Inspectors | 2 |
| 4520XX | Animal Breeders | 2 |
| 472XXX | Brickmasons, Blockmasons, Stonemasons, and Reinforcing Iron and Rebar Workers | 2 |
| 472031 | Carpenters | 2 |
| 472040 | Carpet, Floor, and Tile Installers and Finishers | 2 |
| 472061 | Construction Laborers | 2 |
| 472071 | Paving, Surfacing, and Tamping Equipment Operators | 2 |
| 47207X | Pile-Driver Operators | 2 |
| 47207X | Construction equipment operators except paving, surfacing, and tamping equipment operators | 2 |
| 472080 | Drywall Installers, Ceiling Tile Installers, and Tapers | 2 |
| 472121 | Glaziers | 2 |
| 472130 | Insulation Workers | 2 |
| 472141 | Painters, Construction and Maintenance | 2 |
| 472140 | Painters and Paperhangers | 2 |
| 472150 | Pipelayers, Plumbers, Pipefitters, and Steamfitters | 2 |
| 472XXX | Reinforcing Iron and Rebar Workers | 2 |
| 472181 | Roofers | 2 |
| 472211 | Sheet Metal Workers | 2 |
| 472221 | Structural Iron and Steel Workers | 2 |
| 473010 | Helpers, Construction Trades | 2 |
| 474031 | Fence Erectors | 2 |
| 474051 | Highway Maintenance Workers | 2 |
| 474061 | Rail-Track Laying and Maintenance Equipment Operators | 2 |

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| 475021 | Earth Drillers, Except Oil and Gas | 2 |
| 475031 | Explosives Workers, Ordnance Handling Experts, and Blasters | 2 |
| 475040 | Mining Machine Operators | 2 |
| 493021 | Automotive Body and Related Repairers | 2 |
| 493022 | Automotive Glass Installers and Repairers | 2 |
| 493090 | Miscellaneous Vehicle and Mobile Equipment Mechanics, Installers, and Repairers | 2 |
| 499010 | Control and Valve Installers and Repairers | 2 |
| 499031 | Home Appliance Repairers | 2 |
| 499044 | Millwrights | 2 |
| 499052 | Telecommunications Line Installers and Repairers | 2 |
| 499091 | Coin, Vending, and Amusement Machine Servicers and Repairers | 2 |
| 499094 | Locksmiths and Safe Repairers | 2 |
| 4990XX | Manufactured Building and Mobile Home Installers | 2 |
| 499096 | Riggers | 2 |
| 499098 | Helpers--Installation, Maintenance, and Repair Workers | 2 |
| 511011 | First-Line Supervisors of Production and Operating Workers | 2 |
| 512011 | Aircraft Structure, Surfaces, Rigging, and Systems Assemblers | 2 |
| 512020 | Electrical, Electronics, and Electromechanical Assemblers | 2 |
| 512031 | Engine and Other Machine Assemblers | 2 |
| 512090 | Miscellaneous Assemblers and Fabricators | 2 |
| 513011 | Bakers | 2 |
| 513020 | Butchers and Other Meat, Poultry, and Fish Processing Workers | 2 |
| 513091 | Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders | 2 |
| 513092 | Food Batchmakers | 2 |
| 513093 | Food Cooking Machine Operators and Tenders | 2 |
| 514021 | Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic | 2 |
| 514022 | Forging Machine Setters, Operators, and Tenders, Metal and Plastic | 2 |
| 514023 | Rolling Machine Setters, Operators, and Tenders, metal and Plastic | 2 |
| 514031 | Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic | 2 |
| 514030 | Machine Tool Cutting setters, Operators, and Tenders, Metal and Plastic | 2 |
| 514050 | Metal Furnace Operators, Tenders, Pourers, and Casters | 2 |
| 514070 | Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic | 2 |
| 515113 | Print Binding and Finishing Workers | 2 |
| 516040 | Shoe and Leather Workers and Repairers | 2 |

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| 516050 | Tailors, Dressmakers, and Sewers | 2 |
| 516063 | Textile Knitting and Weaving Machine Setters, Operators, and Tenders | 2 |
| 516064 | Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders | 2 |
| 516093 | Upholsterers | 2 |
| 517011 | Cabinetmakers and Bench Carpenters | 2 |
| 517021 | Furniture Finishers | 2 |
| 517041 | Sawing Machine Setters, Operators, and Tenders, Wood | 2 |
| 517042 | Woodworking Machine Setters, Operators, and Tenders, Except Sawing | 2 |
| 518090 | Miscellaneous Plant and System Operators | 2 |
| 519010 | Chemical Processing Machine Setters, Operators, and Tenders | 2 |
| 519020 | Crushing, Grinding, Polishing, Mixing, and Blending Workers | 2 |
| 519041 | Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders | 2 |
| 519051 | Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders | 2 |
| 519061 | Inspectors, Testers, Sorters, Samplers, and Weighers | 2 |
| 519080 | Medical, Dental, and Ophthalmic Laboratory Technicians | 2 |
| 519111 | Packaging and Filling Machine Operators and Tenders | 2 |
| 519120 | Painting Workers | 2 |
| 519151 | Photographic Process Workers and Processing Machine Operators | 2 |
| 519191 | Adhesive Bonding Machine Operators and Tenders | 2 |
| 519194 | Etchers and Engravers | 2 |
| 519195 | Molders, Shapers, and Casters, Except Metal and Plastic | 2 |
| 519196 | Paper Goods Machine Setters, Operators, and Tenders | 2 |
| 519197 | Tire Builders | 2 |
| 519198 | Helpers--Production Workers | 2 |
| 531000 | Supervisors of Transportation and Material Moving Workers | 2 |
| 533011 | Ambulance Drivers and Attendants, Except Emergency Medical Technicians | 2 |
| 533020 | Bus Drivers | 2 |
| 533030 | Driver/Sales Workers and Truck Drivers | 2 |
| 533041 | Taxi Drivers and Chauffeurs | 2 |
| 534010 | Locomotive Engineers and Operators | 2 |
| 5340XX | Railroad Brake, Signal, and Switch Operators | 2 |
| 536021 | Parking Lot Attendants | 2 |
| 536031 | Automotive and Watercraft Service Attendants | 2 |
| 536061 | Transportation Attendants, Except Flight Attendants | 2 |
| 537030 | Dredge, Excavating, and Loading Machine Operators | 2 |
| 537051 | Industrial Truck and Tractor Operators | 2 |
| 537061 | Cleaners of Vehicles and Equipment | 2 |
| 537062 | Laborers and Freight, Stock, and Material Movers, Hand | 2 |

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|--------|--|---|
| 537063 | Machine Feeders and Offbearers | 2 |
| 537064 | Packers and Packagers, Hand | 2 |
| 537070 | Pumping Station Operators | 2 |
| 537081 | Refuse and Recyclable Material Collectors | 2 |
| 113011 | Administrative Services Managers | 3 |
| 119013 | Farmers, Ranchers, and Other Agricultural Managers | 3 |
| 119061 | Funeral Directors | 3 |
| 119071 | Gaming Managers | 3 |
| 131022 | Wholesale and Retail Buyers, Except Farm Products | 3 |
| 132021 | Appraisers and Assessors of Real Estate | 3 |
| 132081 | Tax Examiners and Collectors, and Revenue Agents | 3 |
| 132082 | Tax Preparers | 3 |
| 151134 | Web Developers | 3 |
| 173020 | Engineering Technicians, Except Drafters | 3 |
| 173031 | Surveying and Mapping Technicians | 3 |
| 194011 | Agricultural and Food Science Technicians | 3 |
| 194031 | Chemical Technicians | 3 |
| 1940XX | Geological and Petroleum Technicians, and Nuclear Technicians | 3 |
| 232011 | Paralegals and Legal Assistants | 3 |
| 254031 | Library Technicians | 3 |
| 259041 | Teacher Assistants | 3 |
| 272030 | Dancers and Choreographers | 3 |
| 2740XX | Broadcast and sound engineering technicians and radio operators | 3 |
| 274021 | Photographers | 3 |
| 274030 | Television, Video, and Motion Picture Camera Operators and Editors | 3 |
| 291141 | Registered Nurses | 3 |
| 291124 | Radiation Therapists | 3 |
| 291126 | Respiratory Therapists | 3 |
| 292021 | Dental Hygienists | 3 |
| 292030 | Diagnostic Related Technologists and Technicians | 3 |
| 292041 | Emergency Medical Technicians and Paramedics | 3 |
| 292061 | Licensed Practical and Licensed Vocational Nurses | 3 |
| 292071 | Medical Records and Health Information Technicians | 3 |
| 312010 | Occupational Therapy Assistants and Aides | 3 |
| 312020 | Physical Therapist Assistants and Aides | 3 |
| 319011 | Massage Therapists | 3 |
| 319091 | Dental Assistants | 3 |
| 319092 | Medical Assistants | 3 |
| 319094 | Medical Transcriptionists | 3 |
| 319096 | Veterinary Assistants and Laboratory Animal Caretakers | 3 |
| 319097 | Phlebotomists | 3 |

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|--------|---|---|
| 331011 | First-Line Supervisors of Correctional Officers | 3 |
| 331012 | First-Line Supervisors of Police and Detectives | 3 |
| 331021 | First-Line Supervisors of Fire Fighting and Prevention Workers | 3 |
| 332011 | Firefighters | 3 |
| 332020 | Fire Inspectors | 3 |
| 333021 | Detectives and Criminal Investigators | 3 |
| 333050 | Police Officers | 3 |
| 339021 | Private Detectives and Investigators | 3 |
| 351011 | Chefs and Head Cooks | 3 |
| 371012 | First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers | 3 |
| 391021 | First-Line Supervisors of Personal Service Workers | 3 |
| 394031 | Morticians, Undertakers, and Funeral Directors | 3 |
| 395011 | Barbers | 3 |
| 395012 | Hairdressers, Hairstylists, and Cosmetologists | 3 |
| 395090 | Miscellaneous Personal Appearance Workers | 3 |
| 397010 | Tour and Travel Guides | 3 |
| 399030 | Recreation and Fitness Workers | 3 |
| 399041 | Residential Advisors | 3 |
| 413041 | Travel Agents | 3 |
| 431011 | First-Line Supervisors of Office and Administrative Support Workers | 3 |
| 433031 | Bookkeeping, Accounting, and Auditing Clerks | 3 |
| 433061 | Procurement Clerks | 3 |
| 434011 | Brokerage Clerks | 3 |
| 434041 | Credit Authorizers, Checkers, and Clerks | 3 |
| 434061 | Eligibility Interviewers, Government Programs | 3 |
| 434131 | Loan Interviewers and Clerks | 3 |
| 434161 | Human Resources Assistants, Except Payroll and Timekeeping | 3 |
| 435061 | Production, Planning, and Expediting Clerks | 3 |
| 436010 | Secretaries and Administrative Assistants | 3 |
| 439011 | Computer Operators | 3 |
| 439XXX | Desktop Publishers | 3 |
| 439041 | Insurance Claims and Policy Processing Clerks | 3 |
| 454011 | Forest and Conservation Workers | 3 |
| 471011 | First-Line Supervisors of Construction Trades and Extraction Workers | 3 |
| 472011 | Boilermakers | 3 |
| 472111 | Electricians | 3 |
| 474011 | Construction and Building Inspectors | 3 |
| 474021 | Elevator Installers and Repairers | 3 |
| 474041 | Hazardous Materials Removal Workers | 3 |
| 491011 | First-Line Supervisors of Mechanics, Installers, and Repairers | 3 |

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|--------|---|---|
| 492011 | Computer, Automated Teller, and Office Machine Repairers | 3 |
| 492020 | Radio and Telecommunications Equipment Installers and Repairers | 3 |
| 492091 | Avionics Technicians | 3 |
| 492092 | Electric Motor, Power Tool, and Related Repairers | 3 |
| 49209X | Electrical and Electronics Installers and Repairers, Transportation Equipment | 3 |
| 492096 | Electronic Equipment Installers and Repairers, Motor Vehicles | 3 |
| 492097 | Electronic Home Entertainment Equipment Installers and Repairers | 3 |
| 492098 | Security and Fire Alarm Systems Installers | 3 |
| 493011 | Aircraft Mechanics and Service Technicians | 3 |
| 493023 | Automotive Service Technicians and Mechanics | 3 |
| 493031 | Bus and Truck Mechanics and Diesel Engine Specialists | 3 |
| 493040 | Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics | 3 |
| 493050 | Small Engine Mechanics | 3 |
| 499021 | Heating, Air Conditioning, and Refrigeration Mechanics and Installers | 3 |
| 499071 | Maintenance and Repair Workers, General | 3 |
| 499043 | Maintenance Workers, Machinery | 3 |
| 499051 | Electrical Power-Line Installers and Repairers | 3 |
| 499060 | Precision Instrument and Equipment Repairers | 3 |
| 49909X | Commercial Divers | 3 |
| 512041 | Structural Metal Fabricators and Fitters | 3 |
| 514010 | Computer Control Programmers and Operators | 3 |
| 514041 | Machinists | 3 |
| 514111 | Tool and Die Makers | 3 |
| 514120 | Welding, Soldering, and Brazing Workers | 3 |
| 515111 | Prepress Technicians and Workers | 3 |
| 515112 | Printing Machine Operators | 3 |
| 518010 | Power Plant Operators, Distributors, and Dispatchers | 3 |
| 518021 | Stationary Engineers and Boiler Operators | 3 |
| 518031 | Water and Wastewater Treatment Plant and System Operators | 3 |
| 519071 | Jewelers and Precious Stone and Metal Workers | 3 |
| 532020 | Air Traffic Controllers and Airfield Operations Specialists | 3 |
| 532031 | Flight Attendants | 3 |
| 535020 | Ship and Boat Captains and Operators | 3 |
| 5350XX | Ship Engineers | 3 |
| 536051 | Transportation Inspectors | 3 |
| 111021 | General and Operations Managers | 4 |
| 1110XX | Legislators | 4 |
| 112011 | Advertising and Promotions Managers | 4 |

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|--------|---|---|
| 112020 | Marketing and Sales Managers | 4 |
| 112031 | Public Relations and Fundraising Managers | 4 |
| 113021 | Computer and Information Systems Managers | 4 |
| 113111 | Compensation and Benefits Managers | 4 |
| 113121 | Human Resources Managers | 4 |
| 113131 | Training and Development Managers | 4 |
| 113051 | Industrial Production Managers | 4 |
| 113061 | Purchasing Managers | 4 |
| 113071 | Transportation, Storage, and Distribution Managers | 4 |
| 119021 | Constructions Managers | 4 |
| 119030 | Education Administrators | 4 |
| 119081 | Lodging Managers | 4 |
| 119141 | Property, Real Estate, and Community Association Managers | 4 |
| 119151 | Social and Community Service Managers | 4 |
| 119161 | Emergency Management Directors | 4 |
| 131011 | Agents and Business Managers of Artists, Performers, and Athletes | 4 |
| 131021 | Buyers and Purchasing Agents, Farm Products | 4 |
| 131023 | Purchasing Agents, Except Wholesale, Retail, and Farm Products | 4 |
| 131030 | Claims Adjusters, Appraisers, Examiners, and Investigators | 4 |
| 131041 | Compliance Officers | 4 |
| 131051 | Cost Estimators | 4 |
| 131070 | Human Resources Workers | 4 |
| 131141 | Compensation, Benefits, and Job Analysis Specialists | 4 |
| 131151 | Training and Development Specialists | 4 |
| 131081 | Logisticians | 4 |
| 131121 | Meeting, Convention, and Event Planners | 4 |
| 131131 | Fundraisers | 4 |
| 131161 | Market Research Analysts and Marketing Specialists | 4 |
| 132011 | Accountants and Auditors | 4 |
| 132031 | Budget Analysts | 4 |
| 132041 | Credit Analysts | 4 |
| 132051 | Financial Analysts | 4 |
| 132052 | Personal Financial Advisors | 4 |
| 132053 | Insurance Underwriters | 4 |
| 132061 | Financial Examiners | 4 |
| 132070 | Credit Counselors and Loan Officers | 4 |
| 151121 | Computer Scientists and Systems Analysts | 4 |
| 151122 | Information Security Analysts | 4 |
| 151131 | Computer Programmers | 4 |
| 15113X | Software Developers, Applications and Systems Software | 4 |
| 151141 | Database Administrators | 4 |
| 151142 | Network and Computer Systems Administrators | 4 |

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|--------|--|---|
| 151143 | Computer Network Architects | 4 |
| 152011 | Actuaries | 4 |
| 171010 | Architects, Except Naval | 4 |
| 171020 | Surveyors, Cartographers, and Photogrammetrists | 4 |
| 172011 | Aerospace Engineers | 4 |
| 1720XX | Biomedical and agricultural engineers | 4 |
| 172041 | Chemical Engineers | 4 |
| 172051 | Civil Engineers | 4 |
| 172061 | Computer Hardware Engineers | 4 |
| 172070 | Electrical and Electronics Engineers | 4 |
| 172110 | Industrial Engineers, including Health and Safety | 4 |
| 172121 | Marine Engineers and Naval Architects | 4 |
| 172131 | Materials Engineers | 4 |
| 172141 | Mechanical Engineers | 4 |
| 1721XX | Mining and Geological Engineers, Including Mining Safety Engineers | 4 |
| 1721YY | Nuclear Engineers | 4 |
| 173010 | Drafters | 4 |
| 191030 | Conservation Scientists and Foresters | 4 |
| 192021 | Atmospheric and Space Scientists | 4 |
| 192030 | Chemists and Materials Scientists | 4 |
| 192040 | Environmental Scientists and Geoscientists | 4 |
| 194021 | Biological Technicians | 4 |
| 194041 | Geological and Petroleum Technicians | 4 |
| 211020 | Social Workers | 4 |
| 211092 | Probation Officers and Correctional Treatment Specialists | 4 |
| 211093 | Social and Human Service Assistants | 4 |
| 212021 | Directors, Religious Activities and Education | 4 |
| 252010 | Preschool and Kindergarten Teachers | 4 |
| 252020 | Elementary and Middle School Teachers | 4 |
| 252030 | Secondary School Teachers | 4 |
| 2590XX | Other Education, Training, and Library Workers | 4 |
| 271010 | Artists and Related Workers | 4 |
| 271020 | Designers | 4 |
| 272012 | Producers and Directors | 4 |
| 272040 | Musicians, Singers, and Related Workers | 4 |
| 273010 | Announcers | 4 |
| 273020 | News Analysts, Reporters and Correspondents | 4 |
| 273031 | Public Relations Specialists | 4 |
| 273041 | Editors | 4 |
| 273042 | Technical Writers | 4 |
| 273043 | Writers and Authors | 4 |
| 291125 | Recreational Therapists | 4 |
| 292010 | Clinical Laboratory Technologists and Technicians | 4 |

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|--------|--|---|
| 3330XX | Fish and Game Wardens | 4 |
| 411012 | First-Line Supervisors of Non-Retail Sales | 4 |
| 413011 | Advertising Sales Agents | 4 |
| 413021 | Insurance Sales Agents | 4 |
| 413031 | Securities, Commodities, and Financial Services Sales Agents | 4 |
| 413099 | Sales Representatives, Services, All Other | 4 |
| 414010 | Sales Representatives, Wholesale and Manufacturing | 4 |
| 419020 | Real Estate Brokers and Sales Agents | 4 |
| 419031 | Sales Engineers | 4 |
| 439081 | Proofreaders and Copy Markers | 4 |
| 439111 | Statistical Assistants | 4 |
| 532010 | Aircraft Pilots and Flight Engineers | 4 |
| 1110XX | Chief Executives | 5 |
| 113031 | Financial Managers | 5 |
| 119041 | Architectural and Engineering Managers | 5 |
| 119111 | Medical and Health Services Managers | 5 |
| 119121 | Natural Science Managers | 5 |
| 131111 | Management Analysts | 5 |
| 151111 | Computer and Information Research Scientists | 5 |
| 1520XX | Mathematicians | 5 |
| 152031 | Operations Research Analysts | 5 |
| 1520XX | Statisticians | 5 |
| 172081 | Environmental Engineers | 5 |
| 191010 | Agricultural and Food Scientists | 5 |
| 191020 | Biological Scientists | 5 |
| 191040 | Medical Scientists | 5 |
| 192010 | Astronomers and Physicists | 5 |
| 193011 | Economists | 5 |
| 193020 | Market and Survey Researchers | 5 |
| 193030 | Psychologists | 5 |
| 1930XX | Sociologists | 5 |
| 193051 | Urban and Regional Planners | 5 |
| 211010 | Counselors | 5 |
| 212011 | Clergy | 5 |
| 231012 | Judicial Law Clerks | 5 |
| 251000 | Postsecondary Teachers | 5 |
| 252050 | Special Education Teachers | 5 |
| 254010 | Archivists, Curators, and Museum Technicians | 5 |
| 254021 | Librarians | 5 |
| 291011 | Chiropractors | 5 |
| 291020 | Dentists | 5 |
| 291031 | Dieticians and Nutritionists | 5 |
| 291041 | Optometrists | 5 |
| 291051 | Pharmacists | 5 |

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|--------|------------------------------|---|
| 291060 | Physicians and Surgeons | 5 |
| 291071 | Physician Assistants | 5 |
| 291081 | Podiatrists | 5 |
| 291181 | Audiologists | 5 |
| 291122 | Occupational Therapists | 5 |
| 291123 | Physical Therapists | 5 |
| 291127 | Speech Language Pathologists | 5 |
| 291131 | Veterinarians | 5 |
| 291151 | Nurse Anesthetists | 5 |

Appendix B: Relevant ACS Cities

| City | State | IPUMS Code | Population | Uber Entry |
|--------------------|-------|------------|------------|----------------|
| Akron | OH | 0010 | 198,006 | August 2014 |
| Anchorage | AK | 0210 | 291,538 | September 2014 |
| Baltimore | MD | 0530 | 602,495 | February 2013 |
| Boston | MA | 0810 | 694,583 | October 2011 |
| Bridgeport | CT | 0830 | 144,900 | October 2015 |
| Chicago | IL | 1190 | 2,705,994 | September 2011 |
| Denver | CO | 1710 | 716,492 | September 2012 |
| Des Moines | IA | 1730 | 216,624 | September 2014 |
| Detroit | MI | 1750 | 672,662 | March 2013 |
| Indianapolis | IN | 2990 | 876,862 | June 2013 |
| Kansas City | KS | 3250 | 152,958 | May 2014 |
| Lexington-Fayette | KY | 3590 | 323,780 | June 2014 |
| Lincoln | NE | 3630 | 287,401 | August 2014 |
| Little Rock | AR | 3650 | 198,606 | November 2014 |
| Los Angeles | CA | 3730 | 3,990,456 | March 2012 |
| Manchester | NH | 3910 | 112,525 | October 2014 |
| McAllen | TX | 3960 | 143,433 | June 2017 |
| Miami | FL | 4110 | 91,718 | June 2014 |
| Milwaukee | WI | 4130 | 592,025 | February 2014 |
| Minneapolis | MN | 4150 | 422,331 | October 2012 |
| Nashville-Davidson | TN | 4410 | 667,560 | December 2013 |
| New York City | NY | 4610 | 8,623,000 | May 2011 |
| Newark | NJ | 4630 | 282,090 | November 2013 |
| Philadelphia | PA | 5330 | 1,584,138 | June 2012 |
| Phoenix | AZ | 5350 | 1,660,272 | August 2013 |
| Portland | OR | 5530 | 650,470 | December 2014 |
| Providence | RI | 5650 | 179,335 | September 2013 |
| Provo | UT | 5660 | 116,702 | September 2015 |
| Richmond | VA | 5870 | 228,783 | August 2014 |
| Saint Louis | MO | 6090 | 302,838 | September 2015 |
| Seattle | WA | 6430 | 744,955 | 2011 |
| Sioux Falls | SD | 6530 | 153,759 | June 2019 |
| Washington D.C. | DC | 7230 | 702,455 | August 2013 |

Appendix C: Relevant BLS Cities

| City | State | BLS Code | Population | Uber Entry |
|---------------------|-------|----------|------------|----------------|
| Anchorage | AK | 1 | 291,538 | September 2014 |
| Phoenix | AZ | 2 | 1,660,272 | August 2013 |
| Little Rock | AR | 3 | 198,606 | November 2014 |
| Los Angeles | CA | 4 | 3,990,456 | March 2012 |
| Denver | CO | 5 | 716,492 | September 2012 |
| Miami | FL | 6 | 91,718 | June 2014 |
| Chicago | IL | 7 | 2,705,994 | September 2011 |
| Indianapolis | IN | 8 | 876,862 | June 2013 |
| Des Moines | IA | 9 | 216,624 | September 2014 |
| Kansas City | KS | 10 | 152,958 | May 2014 |
| Lexington-Fayette** | KY | 11 | 323,780 | June 2014 |
| Baltimore | MD | 12 | 602,495 | February 2013 |
| Boston | MA | 13 | 694,583 | October 2011 |
| Detroit | MI | 14 | 672,662 | March 2013 |
| Minneapolis | MN | 15 | 422,331 | October 2012 |
| Saint Louis | MO | 16 | 302,838 | September 2015 |
| Lincoln | NE | 17 | 287,401 | August 2014 |
| Newark | NJ | 18 | 282,090 | November 2013 |
| New York City | NY | 19 | 8,623,000 | May 2011 |
| Akron | OH | 20 | 198,006 | August 2014 |
| Portland | OR | 21 | 650,470 | December 2014 |
| Philadelphia | PA | 22 | 1,584,138 | June 2012 |
| Nashville-Davidson | TN | 23 | 667,560 | December 2013 |
| Provo | UT | 24 | 116,702 | September 2015 |
| Richmond | VA | 25 | 228,783 | August 2014 |
| Seattle | WA | 26 | 744,955 | 2011 |
| Washington D.C. | DC | 27 | 702,455 | August 2013 |

Appendix D: Detailed Difference-in-Differences Regression

| VARIABLES | (1) | (2) | (3) | (4) |
|-----------------------------------|------------------------|-----------------------|----------------------|------------------------|
| Uber Present | 0.0924 (0.0162) | 0.361** (0.0128) | 0.0276 (0.0524) | |
| Low Skill | -1.155*** (0.00643) | | | |
| <i>(Uber_Present × Low_Skill)</i> | 0.109* (0.0108) | 0.267** (0.00594) | 0.0679* (0.00959) | 0.0596** (0.00251) |
| Constant | 9.375*** (0.00643) | 9.209*** (0.00491) | 9.347*** (0.0211) | 9.358*** (7.15e-05) |
| Skill-by-Year FE | No | Yes | Yes | Yes |
| City FE | No | No | Yes | No |
| City-by-Year FE | No | No | No | Yes |
| Observations | 26,204 | 26,204 | 26,204 | 26,204 |
| R-squared | 0.010 | 0.016 | 0.029 | 0.033 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1