The Effect of Gender and Race on Wage Spillover from Uber's Entrance in United States Cities

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April 21st, 2021

I pledge my honor that this paper represents my own work in accordance with University regulations.
/s/ Andrew Castleman

Special thanks to Ernest Liu, Kecy Wu, Oscar Torres-Reyna, and Devin Sun for the incredible support.

1. Introduction

The 2008 financial crisis crippled the United States labor market with the lowest and highest earners losing employment and wage losses persisted for years. Companies like Uber and Lyft, dependent on an abundant source of freelancers coming out of the crisis, emerged as both an alternative and augmentation to traditional forms of income. Displaced and dismayed workers, particularly millennials disappointed by stunted wages and riddled with debt, looked for an immediate, flexible, and lucrative occupation. This demographic and more continue to shift towards the gig economy today. Now, more than a decade out from the depth of the recession, an estimated three out of every 10 Americans participate as gig workers in some form according to the Federal Reserve's report on the Survey of Household Economic Decision-making ("Report on Economic Well-Being," 2019). As the unemployment rate continued to decline towards historic lows before COVID-19, gig work remained strong, but this time citing less need for primary income and more interest in autonomy, flexibility, and ease of entry.

Due to the more recent development of the gig economy, many of its implications are unexplored and continue to change with the growing firms. The diversity of gigs, a multitude of employers, and differing regulations by city and region make studying the gig economy difficult. As the gig economy has expanded, it has become more feasible to understand the industry, its workers, and its conditions. Gig executives, governments, academics, and workers argue over emerging claims of mistreatment, inequity, and even bias within the underlying technology. Over time, it has been uncovered that gig work suffers from its own forms of racial and gender inequality that have proven difficult to solve. Companies like Uber have actively worked to mitigate these challenges, but they persist despite the seeming impartiality of technology. Researchers continue to work towards understanding these issues within the gig economy to look for ways to inspire growth without continuing to leave the same people behind.

While researchers have moved forward in understanding such characteristics within the gig economy, until more recently, it has been difficult to see how the gig economy has been affecting those outside its circle. As noted, three out of 10 Americans now participate in the gig economy. This critical mass of gig workers has grown large enough that the effects of this minority on the average American worker should be significant in certain contexts. With more than a decade of data available from some of the largest gig employers, it is very possible to begin to make connections between gig work and recent economic phenomena in the more general labor market.

Before COVID-19, the U.S. saw a 50-year record low unemployment of nearly 3.5%, marking one of the tightest labor environments in recent history. Paired with the growth of the gig economy, an underlying pressure emerged for traditional employers to keep up with outside options to maintain their workforce. Where the gig economy lacks in comforts like paid vacation and health insurance, it provides convenience, ease of entry, and most importantly, high average wages. Over the past decade, in cities that record the most gig activity, there has been a wage response to gig alternatives from general low-skill employers.

From a regulatory perspective, companies like Uber and Lyft may be able to argue to regulators across the country that their platforms not only provide so many workers with essential income opportunities, but their model also works to lift all boats. Data seems to suggest this is the case, but what about the other issues? Current empirical research focuses on wage bias and a general labor market wage spillover, but not the connection between the two. This paper specifically aims to explore the macroeconomic gains of low-skilled workers in gig work hot zones to understand the equity of these benefits for previously marginalized groups. I hypothesized that all else equal, the wage spillover effect should be blind to personal characteristics, and the effects of gig entrance should be relatively equal and positive across all groups given broader discrimination protections in the general labor market. Based on analysis in this study, results agree with existing literature that low-skill wages increase after the entrance of gig employers. Regarding biases within this group, results indicate that, despite the efforts of existing government structures, women in low-skill occupations see less benefit from the entrance of gig employers than men to varying statistical significance. Meanwhile, there is no indication of any wage gain disadvantage on a racial basis.

2. Literature Review

Abraham, Haltiwanger, and Sandusky (2019) explore the tremendous growth of the gig economy throughout the past decade. They note the complexity of truly understanding the scale of gig workers under different and changing government classifications. They argue that gig work had been largely underestimated in government reports. Two pieces of evidence point to this conclusion, the first being a dramatic increase in self-employment. Government surveys continually overlook self-employment as an augmentation to primary income, which is very common for gig workers. Secondly, Abraham et. al argue that privately developed sources show conflicting results and have been better indicators of the true gig economy size and growth. For example, BLS data shows a growth of 298% in Ground Passenger Transportation employees between 2010 and 2016. While the exact size and trajectory of the gig economy are difficult to quantify and constantly debated, its growth over the past decade and acceleration into the COVID-19 economy has made it a particularly great candidate for further analysis.

Given the anonymity and autonomy of gig work, it has become a focal point of wage inequality research. With wage decisions largely placed in the hands of blind technology, researchers would expect to find no bias, but they do in many cases. Barzilay and David (2017) find that despite a seemingly level playing field, women's hourly rates average near two-thirds of men's rates, calling it "Discrimination 3.0," where discrimination is no longer just a function of formal barriers and implicit biases. The authors also highlight the ineptitude of current anti-discrimination structures in place to protect against this type of discrimination, pointing out that the independent contractor status of gig workers absolves companies from many antidiscrimination laws such as Title VII. Some states, like California, have been cracking down on the gig giants like Uber to support women on the platform through legislation like the Unruh Civil Rights Act, but this kind of support varies according to state labor laws. These challenges arising from employee classification status support the hypothesis that observed wage discrimination should not persist in wage spillover from gig entrance, as the occupations seeing wage boosts qualify for important additional protections.

Litman et al. (2020) also investigates wage inequality according to gender and discovers similar results. After analyzing 22,271 Mechanical Turk workers who participated in nearly 5 million tasks, he finds that women's hourly earnings were 10.5% lower than men's according to several factors like selecting less lucrative tasks. Cook et al. (2020) echo similar, but smaller (7%), discrepancies at Uber between men and women driver hourly wages. The paper concludes that even in a setting with no explicit gender discrimination according to law, "high opportunity costs for non-paid-work time and gender-based differences in preferences and constraints can sustain a gender pay gap." For example, while gig work offers flexibility, women tend to work in less lucrative hours because that is what their schedule allows. By contrast, men tend to work more hours which include more lucrative periods that women miss out on due to these "gender-based constraints." These findings suggest that the existence of wage discrepancies in a spillover effect will be in part determined by the availability of labor in the context of gender or race-based constraints in the alternative non-gig market. Should availability differ by these contexts, discrepancies are prone to arise despite protections.

Doucette and Bradford (2019) may explain some of the discrepancies between these groups by looking at different motivations for entering and balancing gig work against primary income. They report men and women cite different reasons for entering the gig economy: men focus on increasing current income, while women attempt to counteract income insecurity from their primary occupation. Although these motivations may create different outcomes, Doucette and Bradford (2019) believe this diversity creates greater efficiency in the market overall, where workers match preferences for schedule and context with the most appropriate form of work. Greater productivity emerges from a more efficient allocation of the workforce and its resources to the market's needs. Here lies a possible argument for the largest gig employers in states like California and European countries like France and Italy. While conditions may be equally bad and sometimes worse than traditional labor, the economic benefits of the gig economy are theoretically and empirically significant. Economic efficiency arguments motivate the need for analysis of equity among beneficiaries, as maximum efficiency is oftentimes not the pathway to a healthy, equitable economy.

Sun (2020) explores the macroeconomic relationship between gig workers and traditional employment counterparts. Looking at income data before and after the entrance of Uber in key cities, he finds that wages for low-skilled occupations increase by 26.7% relative to high-skilled occupations over the same period. This suggests that the entrance of large sources of gig work with high wages creates a wage spillover onto the rest of the low-skilled labor market. Sun notes that this phenomenon occurred throughout one of the tightest labor markets in U.S. history, which also likely contributed to the magnitude of the effect. Understanding the equity of this spillover is critical to the efficiency argument against regulation. While some argue employee classification regulation hurts natural efficiency, the resulting protections may be essential for a much broader group than just gig workers.

3. Data

To construct a difference-in-difference analysis, I pull from two sets of data. The first data set tracks the time and location of gig entrance from 2011 to 2015 through Uber, the largest employer of gig workers in the world. I replicate the list created in Sun (2020), which cross-references publicly available data on Uber entrance in cities with those that are comprehensively represented in the American Community Survey. Focusing on Uber allows for feasibility, but it also represents a large percentage of the gig workforce in the U.S. in the low-skilled sector I am focusing on. Koustas (2019) assesses the economic activity of gig workers that offer “common services.” In his data set of 25,000 gig workers that qualified according to this criteria, Uber and Lyft drivers accounted for nearly 90% of the sample. This recent study shows a continued lack of market segmentation and why focusing on Uber can provide meaningful results. Additionally, although Uber may not be wholly representative of the gig workforce today, this paper focuses on the event shock of entering gig work opportunities, of which Uber represented a disproportionate majority at the time of interest.

Secondly, I draw upon the annual American Community Survey (ACS) data from 2007 to 2019 to understand real wage changes following the entrance of the largest gig work platform, Uber. I pull 6 variables from the ACS: (1) total wages, (2) gender, (3) race, (4) city, and (5) survey year, (6) occupation.

The total wages variable in combination with the ACS CPI multiplier using 1999 as a base year will allow me to track real wage changes. Gender is defined as one for male and two for female, which I will manually edit to zero for male and one for female. Race is defined as zero for white and one BIPOC (Black, Indigenous, or Person of Color), or non-white. The occupation variable in conjunction with the Department of Labor's O*NET Job Zones and Descriptions database will allow for a focus on low-skill workers through the "Job Zone" variable. This analysis will focus on occupations that require little to no preparation, or Zone 1. The city and survey year variables align wage increases with exact timelines of large-scale gig entrance. Using low-skilled male and white workers as a control, I conduct a difference-in-difference analysis of the rise in low-skilled wages to answer the question of whether the observed wage bias in the gig economy persists in its supposed market spillover wage increases throughout the U.S. The following tables summarize important statistics for individuals within relevant cities and job zones:

Table 1: Summary Statistics for Regression (1) Data set

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Yearly Mean Wage	1,412,929	48,086	63,822	1	736,000
Log Yearly Mean Wage	1,412,929	10.152	1.297	1	13.509
Sex	1,412,929	0.500	0.500	0	1
Race	1,412,929	0.405	0.491	0	1
Job Zone	1,412,929	2.944	1.024	1	**5**
Census Year	1,412,929			2007	2018
Uber Entry Year	1,412,929			2011	2015
City	1,412,929			1	31

Table 2: Summary Statistics for Regressions (2), (3), (4) Data set (Job Zones ≤ 1)

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Yearly Mean Wage	239,567	20,715	26,144	1	668,000
Log Yearly Mean Wage	239,567	9.367	1.252	1	13.412
Sex	239,567	0.428	0.495	0	1
Race	239,567	0.514	0.499	0	1
Job Zone	239,567	1.000	0.000	1	**1**
Census Year	239,567			2007	2018
Uber Entry Year	239,567			2011	2015
City	239,567			1	31

4. Methodology

I build three data sets to analyze the wage spillover effect after gig entrance and then analyze that spillover in the context of gender and race. To initially clean the ACS data, I first drop all observations from job Zone 5, as these jobs are outliers with respect to the rest of the data set for their highly skilled nature, specific functions, extensive preparation required, and thus disproportionately high wages with respect to even Zone 4 wages. Second, I use the Uber entrance data to create a dummy variable for if Uber has entered the city at the time of each sample. Next, I isolate the event shock by condensing the regression window for each city to plus or minus two years from the event of Uber entrance. Lastly, I generate dummy variables for each group of interest: Zone, gender, and BIPOC identification.

The first data set consists of workers from all four Job Zones to perform a difference-in-difference analysis of wage increases for low-skill versus higher-skill labor after the entrance of gig work. The second and third data sets drop all higher-skill labor to perform a difference-in-difference analysis of wage increases for low-skill men versus low-skill women, low-skill whites versus low-skill non-whites. In each case, I regress the natural logarithm of the mean wage for occupation, gender, or race on a city-year level on variables that represent the event shock, treatment and control groups, and the interaction between the two. The difference-in-difference estimator is represented by the interaction between the two dummy variables for the event shock and group of interest.

4.1 Quantifying the Extent of the Wage Spillover Effect

I first attempt to determine the overall wage effects of Uber entering a specific city. I regress the natural logarithm of mean wage for each panel observation on a constant and dummy variable that represents whether Uber has entered the specific city for each panel sample. I cluster the variance-covariance at the city level, as this should capture the most meaningful differences between samples throughout the panel. Additionally, I run this regression three times with different combinations of relevant fixed effects (FE): city FE, year FE, city and year FE.

$$LNWAGE_{c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \delta_c + \varepsilon_{c,t} \tag{1}$$

$$LNWAGE_{c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \delta_t + \varepsilon_{c,t} \tag{3}$$

$$LNWAGE_{c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \delta_c + \delta_t + \varepsilon_{c,t} \tag{4}$$

I account for several different variables: $LNWAGE_{c,t}$ represents the natural logarithm of the inflation adjusted mean wage collapsed across city and year; β_0 is a constant that represents a base level wage; $UberPresent_{c,t}$ represents a dummy variable that equals one if Uber has entered the city in the sample year; δ_c represents the city level fixed effects, accounting for different conditions across cities; δ_t represents time level fixed effects, accounting for different conditions across time. I choose these fixed effects due to concern for economic recovery following the recession of 2008. I hope to account for this upward trend in wages using these effects. Towards the objective of identifying the overall wage effects of Uber entering a specific city, I focus my study on β_1, which represents the percent change in mean wages following the entrance of Uber into a sampled city.

Next, I attempt to understand the division of wage changes by zone to determine the average gains for low-skilled labor compared to higher skilled counterparts. This works toward identifying the effects of Uber on its target work force. I regress the natural logarithm of mean wage on a city, year, and occupational level on constant, dummy variables for each zone, and the interaction between each zone and the same dummy variable for the presence of Uber in each city. I cluster the variance covariance estimator by city and zone, as effects are likely coupled with geography and job type. Additionally, I run this regression with three combinations of fixed effects: city FE, city and year FE, city and zone-by-year FE. This is a modified replication of one of the premises from Sun (2020) with more focus on the differentiation between wage gains by zone than a generalized high versus low-skill comparison.

$$LNWAGE_{o,c,t} = \beta_0 + \beta_1 Zone1 + \beta_2 Zone2 + \beta_3 Zone3 + \beta_4 Zone4 + UberPresent_{c,t} \times (\beta_5 Zone1 + \beta_6 Zone2 + \beta_7 Zone3 + \beta_8 Zone4) + \delta_c + \varepsilon_{c,t} \tag{4}$$

$$LNWAGE_{o,c,t} = \beta_0 + \beta_1 Zone1 + \beta_2 Zone2 + \beta_3 Zone3 + \beta_4 Zone4 + UberPresent_{c,t} \times (\beta_5 Zone1 + \beta_6 Zone2 + \beta_7 Zone3 + \beta_8 Zone4) + \delta_c + \delta_t + \varepsilon_{c,t} \tag{5}$$

$$LNWAGE_{o,c,t} = \beta_0 + \beta_1 Zone1 + \beta_2 Zone2 + \beta_3 Zone3 + \beta_4 Zone4 + UberPresent_{c,t} \times (\beta_5 Zone1 + \beta_6 Zone2 + \beta_7 Zone3 + \beta_8 Zone4) + \delta_c + \delta_{o,t} + \varepsilon_{c,t} \quad (6)$$

I account for several variables: $LNWAGE_{o,c,t}$ represents the natural logarithm of the inflation adjusted mean wage collapsed across city, year, and occupation; β_0 is a constant that represents a base level wage; $UberPresent_{c,t}$ represents a dummy variable that equals one if Uber has entered the city in the sample year; δ_c represents the city level fixed effects, accounting for different conditions across cities; δ_t represents time level fixed effects, accounting for different conditions across time $\delta_{o,t}$ represents zone-by-year fixed effects that accounts for wage trends across time by skill group. I first look at the trends shown in $\beta_2, \beta_3, \beta_4$ versus $\beta_5, \beta_6, \beta_7, \beta_8$, with the former characterizing additional mean wages from skill relative to Zone 1 by zone and the latter characterizing the additional wage gain after Uber entrance is observed. To determine the relative effect for Uber's primary beneficiaries, Zone 1 workers, compared to high skilled groups, I compare β_5 to β_6 for Zone 2, β_7 for Zone 3, β_8 for Zone 4. Most importantly, I focus my attention on β_5, which represents the marginal effect of Uber entrance of for low-skilled labor, Uber's target partners.

4.2 Quantifying the Extent of Gender Bias in the Wage Spillover

After examining the effects of Uber entrance on different occupational wages by skill, I turn back to the original question of whether previously researched biases within the gig economy exist on the macroeconomic scale in these wage changes. To accomplish this with respect to gender bias, I isolate the most applicable skill group, Zone 1, for more careful study. I regress the natural logarithm of mean wage for each Zone 1 panel observation at the gender, city, and year level on a constant, the same dummy variable for the presence of Uber at the time of the survey, a dummy variable indicating the sample gender, and the interaction between these two dummy variables. The variance-covariance is clustered at the city and gender level for the same reasons already discussed. Additionally, I run this regression with five combinations of fixed effects: no FE, city FE, year FE, city and year FE, city and gender-by-year FE.

$$LNWAGE_{g,c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \beta_2 Female_g + \beta_3\left(UberPresent_{c,t} \times Female_g\right) + \delta_c + \varepsilon_{g,c,t} \quad (7)$$

$$LNWAGE_{g,c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \beta_2 Female_g + \beta_3\left(UberPresent_{c,t} \times Female_g\right) + \delta_t + \delta_c + \varepsilon_{g,c,t} \quad (8)$$

$$LNWAGE_{g,c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \beta_2 Female_g + \beta_3\left(UberPresent_{c,t} \times Female_g\right) + \delta_{g,t} + \delta_c + \varepsilon_{g,c,t} \quad (9)$$

I account for several variables: $LNWAGE_{o,c,t}$ represents the natural logarithm of the inflation adjusted mean wage collapsed across city, year, and gender; β_0 is a constant that represents a base level wage; $UberPresent_{c,t}$ represents a dummy variable that equals one if Uber has entered the city in the sample year; $Female_g$ represents a dummy variable that equals one if the sample is female; δ_c represents the city level fixed effects; δ_t represents time level fixed effects; $\delta_{g,t}$ represents gender-by-year fixed effects, accounting for wage trends across genders over time. I focus my attention on β_3 and $\beta_1 + \beta_3$. β_3 characterizes the marginal effect of gender on mean wage after the entrance of Uber while $\beta_1 + \beta_3$ characterizes the total average wage differential for females after Uber entrance. While the significance of β_3 allows for comparison of wage benefits with respect to men, the total wage differential also gives a general indication of whether there is a positive or negative effect on wages for women.

4.3 Quantifying the Extent of Racial Bias in the Wage Spillover

Lastly, I examine whether racial biases exist in the macroeconomic effect of Uber entrance. I define racial identification as either white or BIPOC. To understand the presence of any racial bias in wage effects, I regress the natural logarithm of mean wage for each Zone 1 panel observation at the race, city, and year level on a constant, the same dummy variable for the presence of Uber at the time of survey, a dummy variable indicating BIPOC identification, and the interaction between these two dummy variables. The variance-covariance is clustered at the city and race level for the same reasons already discussed. Additionally, I run this regression with five combinations of fixed effects: no FE, city FE, year FE, city and year FE, city and race-by-year FE.

$$LNWAGE_{r,c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \beta_2 BIPOC_r + \beta_3\left(UberPresent_{c,t} \times BIPOC_r\right) + \delta_c + \varepsilon_{r.c,t} \tag{10}$$

$$LNWAGE_{r,c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \beta_2 BIPOC_r + \beta_3\left(UberPresent_{c,t} \times BIPOC_r\right) + \delta_t + \delta_c + \varepsilon_{r.c,t} \tag{11}$$

$$LNWAGE_{r,c,t} = \beta_0 + \beta_1 UberPresent_{c,t} + \beta_2 BIPOC_r + \beta_3\left(UberPresent_{c,t} \times BIPOC_r\right) + \delta_{r,t} + \delta_c + \varepsilon_{r.c,t} \tag{12}$$

I account for several variables: $LNWAGE_{o,c,t}$ represents the natural logarithm of the inflation adjusted mean wage collapsed across city, year, and race; β_0 is a constant that represents a base level wage; $UberPresent_{c,t}$ represents a dummy variable that equals one if Uber has entered the city in the sample year; δ_c represents the city level fixed effects; δ_t represents time level fixed effects; $\delta_{r,t}$ represents race-by-year fixed effects, accounting for wage trends across race over time. Similar to the gender case, I focus my attention on β_3 and $\beta_1 + \beta_3$. β_3 characterizes the marginal effect of race on the mean wage after the entrance of Uber, while $\beta_1 + \beta_3$ characterizes the total average wage change for people who identify as BIPOC after Uber entrance. I can perform similar analysis as in the gender case to determine the significance of racial bias for BIPOC.

The validity of each difference-in-difference analysis relies on the consideration of three critical assumptions. First, the intervention must be unrelated to outcome at baseline. Here, I assume the introduction of Uber into cities is a firm-centric profit-driven decision that is more likely driven by customer demand than labor demand. This can be exhibited by the early introduction into cities with high or low labor costs, such as New York and Los Angeles versus Minneapolis and Philadelphia. Thus, I assume Uber's entrance is otherwise unbiased by general wages at baseline. Second, the treatment and control groups must have parallel trends in outcome. While perfect parallel trends are unlikely in practice, the general wage trends with Uber entry normalized are similar for each grouping. As expected, there is wage growth for all groups throughout this period as the U.S. economy recovered from mean wage declines during the recession from 2007-2008. Thus, it is important to control for this wage growth through fixed effects. Parallel trends are also exhibited through graphing wage trends in results below. Third, the outcomes of one sample should be unaffected by the treatment or control of another sample. Here, I assume the entrance of Uber in one city does not affect outcomes in other cities. This is one area of concern due to more general wage policies for employers operating in multiple cities or employers anticipating Uber entrance. Anticipation is less likely because of the immediate nature of Uber entrance, unpredictability of its announcement, and the profit implications of raising wages without increased labor demand. Employers operating in multiple locations will also most likely not significantly impact results because blanket wage structure is uncommon, although possible.

5. Results and Discussion

5.1 Quantifying the Extent of the Wage Spillover Effect

Table 3 and Models (1), (2), and (3) explore the more general question of whether Uber's entrance across cities is significantly correlated with an increase in mean wages. Model (1) is run using city fixed effects, Model (2) is run with year fixed effects, and Model (3) includes city and year fixed effects. Models (1) and (2) show a coefficient for $UberPresent_{c,t}$ that is statistically significant at the 1% level and 5% level respectively. We interpret this as Uber's entrance into a new city is correlated with a 12.0% and 9.00% increase in overall mean wages respectively. Model (3), however, which accounts for city and year fixed effects, is likely the most accurate model. Accounting for these fixed effects, the significance of Uber entrance disappears and becomes near zero, or a 1.49% wage increase. While the results of each of these models are difficult to draw any strong conclusions from, they do indicate there is likely some relationship between Uber's entrance into a city and broader wage growth.

Table 3: General Wage Results

VARIABLES	(1)	(2)	(3)
UberPresent	0.120***	0.0900**	0.0149
	(0.0273)	(0.0378)	(0.0575)
City FE	Yes	No	Yes
Year FE	No	Yes	Yes
Observations	38,072	38,072	38,072
R-squared	0.010	0.020	0.010

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficients from Models (1) and (2) indicate there is correlation between Uber entrance of overall wage growth, but Model (3) suggests there are more complex underlying features in the data that can better explain the wage growth. In order to determine the existence of potential racial or gender biases, it is important to consider the more complex elements of Uber and its market, such as the impact of skill.

To consider the more specific impacts of Uber on mean wages, I observe the change in wages over time by skill group, where an increase in zone from one to four represents an increase in skill, according to the BLS. This gives a more accurate picture of Uber's impact, given the specific low-skill labor market in which Uber typically operates. I conduct a difference-in-difference analysis with several combinations of fixed effects: city fixed effects (4), city and year fixed effects (5), and city and zone-by-year fixed effects (6). Table 4 provides the coefficients for each zone and the difference-in-difference estimator, which is the coefficient of the interaction term between $UberPresent_{c,t}$ and zone. The difference-in-difference estimator can be interpreted as the marginal change in wages for each zone relative to that same zone without Uber entrance. A more detailed set of regressions with more combinations of fixed effects is located in Appendix D. Model (4) results in coefficients for the interaction terms between $UberPresent_{c,t}$ and zone of 26.1%, 1.47%, 4.67%%, and 4.71% as skill increases from Zone 1 to Zone 4, respectively. For significance, only Zone 1, indicating low-skill, shows any significance, which is at the 5% level. Adding year fixed effects to Model (4) yields Model (5), resulting in interaction term coefficients of 20.8%, -3.26%, 0.00%, and -0.25% as skill zone increases. None of these coefficients are significant at the 10% level, however, Zone 1 is, again, the most statistically different from zero. Model (6), which removes year FE and adds skill-by-year FE, results in coefficients for the interaction terms of 12.4%, -10.5%, -0.22%, and 12.2% as skill increases. None of these coefficients are significant at the 10% level, but, like Model (5), Zone 1 is the most statistically different from zero compared to other skill zones.

Table 4: Wage Spillover Results

VARIABLES	(4)	(5)	(6)
Zone 1	omitted	omitted	omitted
Zone 2	0.791***	0.789***	omitted
	(0.0838)	(0.0857)	
Zone 3	1.327***	1.325***	omitted
	(0.0858)	(0.0857)	
Zone 4	2.093***	2.094***	omitted
	(0.0859)	(0.0859)	
UberPresent × Zone 1	0.261**	0.208	0.124
	(0.124)	(0.134)	(0.179)
UberPresent × Zone 2	0.0147	-0.0326	-0.105
	(0.0424)	(0.0655)	(0.0725)
UberPresent × Zone 3	0.0467	0.000833	-0.00218
	(0.0509)	(0.0712)	(0.0822)
UberPresent × Zone 4	0.0471	-0.00250	0.122
	(0.0794)	(0.0714)	(0.0825)
City FE	Yes	Yes	Yes
Year FE	No	Yes	No
Skill-by-year FE	No	No	Yes
Observations	38,072	38,072	38,072
R-squared	0.059	0.060	0.053

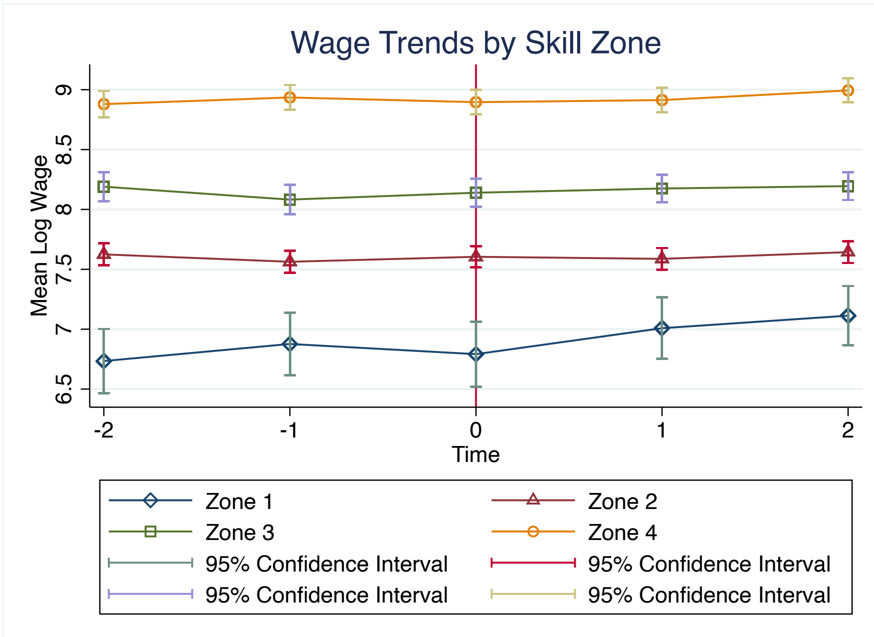
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Model (4), the difference-in-difference estimators suggest that Uber's entrance into a city leads to a growth in wages for all zones, although to a much lesser degree as skill reaches Zones 2, 3, and 4. Model (5) accounts for the same city fixed affects and adds year fixed effects. This leads to a decrease in the difference-in-difference estimator for each zone. Zone 1 loses its statistically significant wage increase at the 5% or 10% level, whereas Zones 2, 3, and 4 become negative or very close to zero. This change is due to the addition of year fixed effects, which accounts for variation in the wage variable over time that is not attributable to the presence of Uber. This suggests much of the variation in the wage can be explained by organic wage growth likely fueled by economic growth and the recovery of wages following the recession, each not attributable to the presence of Uber. It is worth noting that although the difference-in-difference estimator for Zone 1 is no longer significant, it is still well above no change at 20.8% and significantly higher and more statistically different from zero than its counterparts. This suggests, as expected, that the effect of Uber on wages is higher for low-skilled labor than other skill groups, while the magnitude of this effect is difficult to determine with certainty using the existing data.

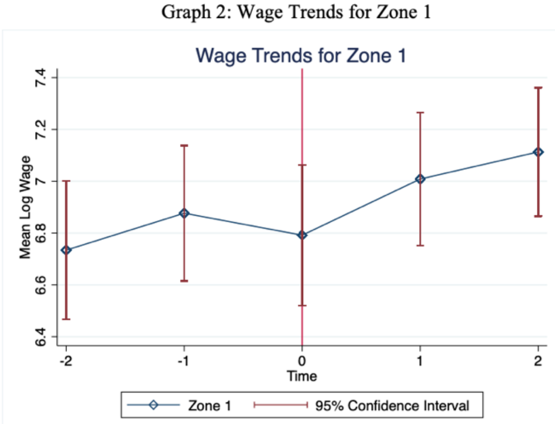
Model (6) is likely the most accurate model, as it accounts for skill-by-year fixed effects in addition to city fixed effects, capturing organic wage growth for each zone throughout the recovery from the Great Recession and city level trends. While the coefficient for Zone 1 is still positive at 12.4%, it is even less statistically significant, weakening our earlier claim. Additionally, we observe an oddly significant gain in wages for the highest skill group in Zone 4, which now suggests a 12.2% wage increase with the entrance of Uber. This growth may be attributed to Uber strategically entering cities with potential for high-skilled wage growth, given that their platform needs passengers in addition to drivers, but it is still unlikely this can explain such significant wage growth. Nonetheless, it is almost certainly not part of any wage spillover, as Uber driver wages are not high enough to impact wage growth in Zone 4.

Despite the insignificance of results in some models, they depict a broader picture of wage growth according to zone after Uber entrance. Graph 1 provides a general picture of wage trends by zone with Uber entry point normalized to zero. First, we observe relatively parallel trends prior to Uber entry for each zone, bolstering our methodology assumptions. Second, there is a clear increase in wages after Uber entry, although to varying degrees of certainty. The graph echoes the conclusions of regression data: Zone 1 exhibits larger increases in wages, but a high variance limits confidence. Graphs 2, 3, 4, and 5, also add to this notion. The scaling of the y-axis in each graph indicates the variance of the wage for each group. While Zone 1 shows strong growth after Uber entrance, its wide confidence intervals nearly encompass its full range of growth for both years observed after entry. Despite lower variance for higher skill zones, confidence intervals do encompass the full range of growth, making it difficult to distinguish an causal implication of Uber for these groups. The difference-in-difference estimators from the various models above and graphical results below seem to agree that Zone 1 sees the greatest gains from Uber entrance to varying degrees of economic and statistical certainty. Returning to the original question of whether Uber's impact on wages has led to further biases, I focus on those most affected for more careful analysis, which appears to be in this lowest skill group.

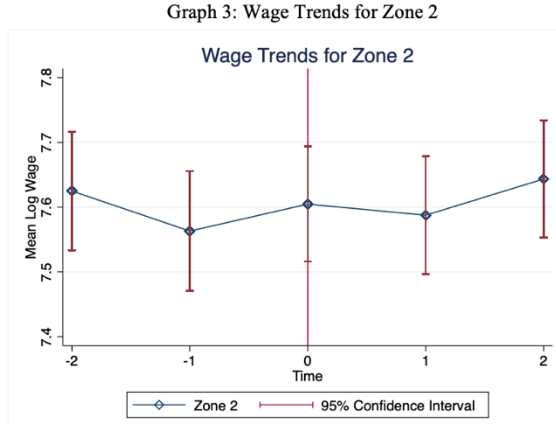
Graph 1: Wage Trends by Skill Zone with Uber Entry Normalized to Time = 0



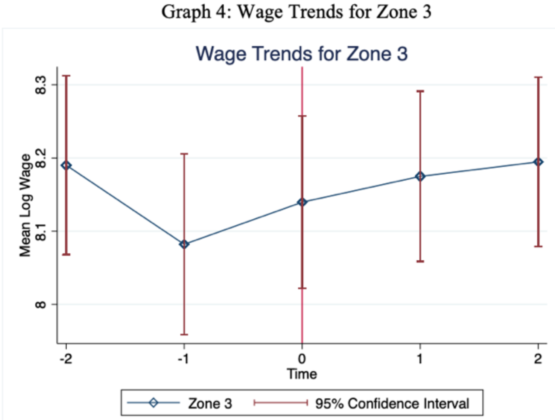
Graph 2: Wage Trends for Zone 1



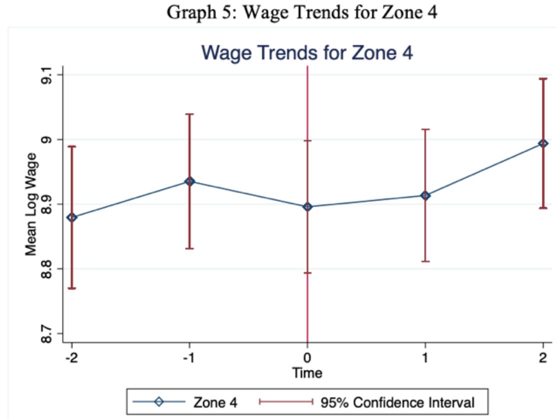
Graph 3: Wage Trends for Zone 2



Graph 4: Wage Trends for Zone 3



Graph 5: Wage Trends for Zone 4



5.2 Quantifying the Extent of Gender Bias in the Wage Spillover Effect

To further understand the potential biases of any Uber wage spillover effect, I conduct another difference-in-differences analysis. Here, I focus on the lowest skill group and the difference-in-difference estimator is the interaction between gender (female) and the presence of Uber at the time of sample. The difference-in-difference estimator can be interpreted as the marginal change in wages for each gender relative to that same gender without Uber entrance. I run another set of regressions: with city fixed effects (7), with city and year fixed effects (8), and with city and gender-by-year fixed effects (9). Model (7) results in a difference-in-difference estimator of -26.0% at the 1% significance level. Model (8) results in a difference-in-difference estimator of -26.0% at the 1% significance level. Model (9) results in a difference-in-difference estimator of -23.3% that is not significant at the 10% level.

Table 5: Wage Spillover Results for Zone 1 by Gender

VARIABLES	(7)	(8)	(9)
UberPresent	0.496***	0.297**	0.284*
	(0.0749)	(0.129)	(0.158)
Female	-0.116	-0.116*	
	(0.0692)	(0.0682)	
(UberPresent ×	-0.260***	-0.260***	-0.233
Female)	(0.105)	(0.103)	(0.211)
City FE	Yes	Yes	Yes
Year FE	No	Yes	No
Gender-by-year FE	No	No	Yes
Observations	682	682	682
R-squared	0.253	0.285	0.301

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results in Table 5 suggest some correlation between gender and wage increases for low-skilled workers after the entrance of Uber. Once again, it appears that adding more fixed effects reduces the significance of this correlation, suggesting that there is much more complexity to the issue than presented through this set of regressions. Specifically, the dramatic change when adding gender-by-year fixed effects suggests that most of the variation in wages can be attributed to trends in wages by gender across time rather than Uber entrance. Despite the reduction in significance, Model (9), which is likely the most accurate model for its incorporation of both gender-by-year and city level fixed effects, still reports a highly negative coefficient. Additionally, looking at the total wage gain as a result of Uber entrance by adding each coefficient by model, we observe that there is a net positive effect for Models (7) and (9) and a net negative effect for Model (8). Model (9) results in a net wage effect for women of 5.1%. While this is still a positive effect, it is very small compared to the male coefficient of 28.4%. Generally, there is some evidence, although not statistically significant in the most probable model, of gender bias in the wage effects of Uber entrance on low-skilled labor. The consistently negative coefficient of the difference-in-difference estimator seems to suggest some bias, but as with determining the specific wage effects, it is not possible to confidently determine the causal relationship without more statistically significant coefficients.

These findings extend and echo the conclusions from Litman et al. (2020) and Cook (2020), who find, similarly, that women are seeing less benefit from the rise of the gig economy than men. While women do appear to gain from the entrance of Uber, this is on a much smaller scale. Despite the different, broader context and population of this study, the inequities are likely explained by similar societal and economic structures proposed by Cook (2020) or Doucette and Bradford (2019). Cook (2020) puts forth the theory that gender-based constraints confine women to certain roles and can limit mobility. If a wage spillover is derived from increased competition in the labor market, these gender-based constraints may limit women from taking advantage of this full range of competition and thus limit its benefits. Doucette and Bradford (2019) outline the different preferences of men and women that result in different task selection inside and outside of the gig economy. The above wage discrepancy may partially be explained by certain tasks preferred by women lacking transferability between gig and non-gig work. Again, this would limit their ability to take advantage of a more competitive labor market with the entrance of gig work.

5.3 Quantifying the Extent of Racial Bias in the Wage Spillover Effect

To further understand the racial biases of any Uber wage spillover effect, I conduct a third difference-in-differences analysis. Again, I focus on the lowest skill group and the difference-in-difference estimator is the interaction between race (BIPOC) and the presence of Uber at the time of sample. The difference-in-difference estimator can be interpreted as the marginal change in wages for each race relative to that same race without Uber entrance. I run another set of regressions: with city fixed effects (10), with city and year fixed effects (11), and with city and race-by-year fixed effects (12). Model (10) results in a difference-in-difference estimator of 12.4%. Model (11) results in a difference-in-difference estimator of 12.4%. Model (12) results in a difference-in-difference estimator of 19.2%. None of these estimators are statistically significant at the 10% level.

Table 6: Wage Spillover Results for Zone 1 by BIPOC Status

VARIABLES	(10)	(11)	(12)
UberPresent	0.310***	0.127	0.0930
	(0.0815)	(0.141)	(0.173)
BIPOC	-0.222***	-0.223***	
	(0.0753)	(0.0744)	
(UberPresent × BIPOC)	0.124	0.124	0.192
	(0.114)	(0.113)	(0.231)
City FE	Yes	Yes	Yes
Year FE	No	Yes	No
BIPOC-by-year FE	No	No	Yes
Observations	682	682	682
R-squared	0.200	0.108	0.243

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results in Table 6 suggest there is little correlation between race and wage increases for low-skilled workers after the entrance of Uber. While the coefficients on all interaction terms are positive, none are statistically significant to any degree. The addition of year fixed effects from Model (10) to Model (11) does not change the difference-in-difference estimator, but dramatically reduces the coefficient on $UberPresent_{c,t}$ and its statistical significance declines, like previous models. This suggests some of the variability in wages is, once again, explained by changes across time. This is further emphasized from Model (11) to Model (12) as accounting for wage trends at the race level reduces this coefficient again. Generally, these results suggest there is little evidence for racial bias in wage effects of Uber entrance due to the very insignificant coefficients for the difference-in-difference estimator.

Although there is very little statistical significance to these results, those who identify as BIPOC appear to benefit from Uber entrance at a greater level than whites. Additionally, despite this presumed benefit ranging from 12.4% to 19.2%, the racial wage gap of over 22% in Models (10) and (11) show any benefit from Uber entrance does not make up for other economic disadvantages for BIPOC relative to whites. While literature on the racial makeup of the gig economy is limited, this marginal benefit could be explained by similar principles outlined in gender-based research. While few would argue there are race-based constraints on white workers, the preferences argument from Doucette and Bradford (2019) most likely applies. Whites may prefer occupations that are less transferable to the gig economy and therefore experience less direct benefit from its introduction and increased labor demand in the broader economy.

6. Limitations

There are a variety of potential limitations that may have impacted the confidence of this study. First, the availability of data limits the scope of this study, as it relies on Uber data that is publicly available. The list of cities compiled from Uber's announcement of entry only consists of U.S. cities and is confined to 31 cities with enough data for reliable regressions shown in Appendix A. Confinement to these cities in addition to less availability of data for the lowest skill group (Zone 1) relative to higher skill groups led to high variance in results for this key population segment. Outside of Zone 1, the results indicate that the larger sample size allows for much less variance in subsequent wage effects. Should more data be collected specific to labor in Zone 1, inquiries into this subject could be studied with more certainty. Using this methodology also ignores all gig presence outside of metropolitan areas. Although the ACS data used in conjunction with the Uber data focused on the specific listed cities, it is important to consider the difference in job zone distributions across urban, suburban, and rural areas throughout the U.S. This could have a dramatic impact on the real wage effects and resulting biases that may exist as a result of the gig economy.

Furthermore, this study heavily relies on the assumption of Uber dominance throughout the early gig labor market in each city. While this was largely true at the point of each event shock, as outlined by Koustas (2019), Uber certainly was not the only gig employer throughout this period, and not always the largest. A significant development of the gig labor market before the identified point of entry for the purpose of this paper would lead to artificially low observed wage effects in the data presented.

Lastly, there are many variables that vary significantly across the U.S. that may create opportunities for omitted variable bias in this context. The decentralized government response to gig labor continues to be a challenge for understanding the country level response to gig companies. As legislation develops at the state and city level, effects can vary significantly based on geography and year in which key legislation becomes law. The complex economic differences due to demographics, legislation, and other factors in cities and states across the country also presented challenges for Uber as they chose where to enter. These business decisions present confounding variables, as Uber makes strategically timed decisions for when and where to enter a new market. One would assume markets with less competitive low-skill labor markets and overall economic growth would be attractive targets. Accounting for this type of strategy is difficult given the availability of relevant data, and these endogenous variables can skew wage increases because of Uber upward.

Additionally, there is potential for Uber entrances in early cities to affect results in cities where Uber enters later in the period of study. First, it is possible for employers in cities with a more recent Uber entrance to learn from historical trends and preemptively initiate wage increases before an official entrance. This is less likely, as it is difficult to anticipate Uber's entrance and it begins with immediate effect. Second, the same effect can result from nationally mandated wage increases for firms with employees in different cities across the country and a more blanket wage policy. These firms may have increased wages when locations with an early entrance of Uber encountered increasing labor demand and anticipated an increase in demand elsewhere. This anticipation would skew results downward for cities where Uber enters later in the period of study. This issue is more likely to create any significant effects. Several large employers of lower skill groups, such as Walmart and Amazon, have initiated more widespread wage policies which may impact results for later cities.

There are also many potential areas for further study, especially surrounding the limitations and potentially confounding variables presented above. In response to the smaller sample size of Zone 1 workers, a different subset of the lower skill labor population could be identified and studied to produce less noisy results and reach more confident conclusions. In addition, as new legislation passes in more progressive states like California and New York, the labor market will experience new event shocks that shift the balance of power between gig companies, like Uber, and more traditional employers. Continuing to combine proprietary data from gig companies with macroeconomic data surrounding the health of the labor market with be critical in assessing the success and failure of new policy. As companies like Uber entice more and more people to become part of their lucrative market, it becomes more important to understand the macroeconomic consequences as they grow in significance. The variation in response across different cities and states lends itself to an experiment studying the effects of different solutions and their efficacy.

7. Conclusion

Theoretical and empirical research from Koustas (2019) and Sun (2020) respectively indicate that the macroeconomic effect of the gig economy on wages is significant throughout the U.S., while other empirical research, like Barzilay (2017) and Cook (2020), shows clear inequity in wage rates between certain groups throughout the gig economy. This remains an incredibly important topic as the gig economy continues to grow and evolve into a core part of the U.S. and world economies. This study aims to analyze the macroeconomic effects of Uber's presence in markets across the U.S. to further understand the intersection between Uber's growth alongside the broader economy and the observed inequity within its programs and others like it.

My findings appear to support the conclusions of Koustas (2019) and Sun (2020), which explore the growing significance of macroeconomic effects stemming from the gig economy. My initial findings support the claim that the entrance of the gig economy, represented by the entrance of Uber, can have a positive effect on mean wages for low-skilled workers. I run a difference-in-differences analysis similar to Sun (2020), regressing the natural logarithm of mean wages on the interaction terms between job skill zones and an indicator variable for the presence of Uber in the sample city. While the statistical significance of the difference-in-difference estimators decline when accounting for city and skill-based trends over time, there appears to be generally positive correlation between Uber entrance and mean wage increases. Also, there appears to be a relationship between decreasing skill level and wage boosts after Uber entrance, where the lowest skill group sees significantly more gains post Uber entrance than higher skill groups. While this paper largely agrees with the notion of some positive impact of Uber on mean wages, the extent of this impact is still unclear due to statistical uncertainty.

My findings also appear to extend the work of Doucette and Bradford (2019), which seeks to understand the possibilities for inequity in the gig economy found the work of Barzilay (2017) and Cook (2020). After running a difference-in-differences analysis by regressing the natural logarithm of mean wages for low-skilled workers on the interaction between the gender and an indicator variable for the presence of Uber in the sample city, I find two results. First, there appears to be a wage boost for both low-skilled men (28.4%) and women (5.1%) after the entrance of Uber at a low level of statistical significance. Secondly, there is a clear pattern of bias in this wage increase towards men, who gain 23.3% more than women, but accounting for city and gender level wage trends leads to a less certain result. Similar to the value of general wage effects, there appears to be a pattern of bias, yet the extent of this issue is uncertain given the noise in current results. This noise is largely attributed to the lower sample size in the lowest skill group.

Meanwhile, it is pleasing to see in my findings that the existence of racial inequity after the entrance of Uber is not attributable to Uber to a statistically significant degree. This was generally expected, as most current literature focused on gender-based concerns. Coefficients indicate that if inequity does exist, it actually boosts wages of this group disproportionately. Given that this group already suffers from a clear reduction in mean wages more generally, I would argue this is a net positive impact. Nonetheless, the statistically insignificant coefficients of the difference-in-difference estimators do not give strength to such claims.

Thus, the findings of this paper generally support the hypothesis that the gender inequities observed within gig companies may extend to the broader macroeconomic effects of the gig economy, while racial inequities largely do not exist. This is not to say algorithmic biases in one ride share program leads to systemic wage inequity, but there seems to be a broader gender bias within the space that has extended outside its own footprint. Existing literature suggests these trends may extend from gender-based constraints around the most lucrative working hours or task selection. Many of these constraints are out of the control for gig companies and require alternative solutions or governments attention. This macroeconomic effect is significant for companies like Uber and Lyft as they face regulatory boards across the world. I initially hypothesized that current anti-discrimination laws and other worker's protections in the broader economy would not allow this trend to emerge, but this seems not to be the case. This could be explained by the pursuit of gig companies to expand into areas with more relaxed labor laws, thus giving more opportunity for gender wage gaps to materialize on a broader scale. As the gig economy continues to grow into its role in the world economy, it will become increasingly important for governments to keep up and not leave certain groups behind.

8. References

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Appendix A: Relevant ACS Cities

City	State	Population	Uber Entry	ID
Anchorage	AK	291,538	Sep-14	1
Phoenix	AZ	1,660,272	Aug-13	2
Little Rock	AR	198,606	Nov-14	3
Los Angeles	CA	3,990,456	Mar-12	4
Denver	CO	716,492	Sep-12	5
Miami	FL	91,718	Jun-14	6
Chicago	IL	2,705,994	Sep-11	7
Indianapolis	IN	876,862	Jun-13	8
Des Moines	IA	216,624	Sep-14	9
Kansas City	KS	152,958	May-14	10
Lexington-Fayett	KY	323,780	Jun-14	11
Baltimore	MD	602,495	Feb-13	12
Boston	MA	694,583	Oct-11	13
Detroit	MI	672,662	Mar-13	14
Minneapolis	MN	422,331	Oct-12	15
Saint Louis	MO	302,838	Sep-15	16
Lincoln	NE	287,401	Aug-14	17
Newark	NJ	282,090	Nov-13	18
New York City	NY	8,623,000	May-11	19
Akron	OH	198,006	Aug-14	20
Portland	OR	650,470	Dec-14	21
Philadelphia	PA	1,584,138	Jun-12	22
Nashville-Davidson	TN	667,560	Dec-13	23
Providence	RI	179,335	Sep-13	24
Provo	UT	116,702	Sep-15	25
Richmond	VA	228,783	Aug-14	26
Seattle	WA	744,955	2011	27
Milwaukee	WI	592,025	Feb-14	28
Washington D.C.	DC	702,455	Aug-13	29

Appendix B:

Table 3: General Wage Results

	(1)	(2)	(3)	(4)
VARIABLES				
UberPresent	0.122***	0.120***	0.0900**	0.0149
	(0.0238)	(0.0273)	(0.0378)	(0.0575)
City FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Observations	38,072	38,072	38,072	38,072
R-squared	0.005	0.010	0.020	0.010

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C:

Table 4: Wage Spillover Results

VARIABLES	(5)	(6)	(7)	(8)	(9)
Zone 1	omitted	omitted	omitted	omitted	omitted
Zone 2	0.797***	0.791***	0.797***	0.789***	omitted
	(0.0826)	(0.0838)	(0.0841)	(0.0857)	
Zone 3	1.337***	1.327***	1.337***	1.325***	omitted
	(0.0859)	(0.0858)	(0.0861)	(0.0857)	
Zone 4	2.104***	2.093***	2.108***	2.094***	omitted
	(0.0841)	(0.0859)	(0.0862)	(0.0859)	
UberPresent × Zone 1	0.261**	0.261**	0.281**	0.208	0.124
	(0.119)	(0.124)	(0.128)	(0.134)	(0.179)
UberPresent × Zone 2	0.0182	0.0147	0.0416	-0.0326	-0.105
	(0.0422)	(0.0424)	(0.0497)	(0.0655)	(0.0725)
UberPresent × Zone 3	0.0476	0.0467	0.0721	0.000833	-0.00218
	(0.0549)	(0.0509)	(0.0571)	(0.0712)	(0.0822)
UberPresent × Zone 4	0.0500	0.0471	0.0686	-0.00250	0.122
	(0.0478)	(0.0794)	(0.0575)	(0.0714)	(0.0825)
City FE	No	Yes	No	Yes	Yes
Year FE	No	No	Yes	Yes	No
Skill-by-year FE	No	No	No	No	Yes
Observations	38,072	38,072	38,072	38,072	38,072
R-squared	0.051	0.059	0.052	0.060	0.053

Standard errors in parentheses

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

Appendix D:

Table 5: Wage Spillover Results for Zone 1 by Gender

VARIABLES	(9)	(10)	(11)	(12)	(13)
UberPresent	0.501***	0.496***	0.359***	0.297**	0.284*
	(0.081)	(0.075)	(0.128)	(0.129)	(0.158)
Female	-0.116	-0.116	-0.116	-0.116*	
	(0.0717)	(0.069)	(0.0740)	(0.068)	
(UberPresent ×	-0.260**	-0.260***	-0.260**	-0.260***	-0.233
Female)	(0.130)	(0.105)	(0.112)	(0.103)	(0.211)
City FE	No	Yes	No	Yes	Yes
Year FE	No	No	Yes	Yes	No
Gender-by-year FE	No	No	No	No	Yes
Observations	682	682	682	682	682
R-squared	0.088	0.253	0.118	0.285	0.301

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E:

Table 6: Wage Spillover Results for Zone 1 by BIPOC Status

VARIABLES	(14)	(15)	(16)	(17)	(18)
UberPresent	0.314***	0.310***	0.179	0.127	0.093
	(0.072)	(0.081)	(0.136)	(0.141)	(0.173)
BIPOC	-0.223**	-0.222***	-0.223***	-0.223***	
	(0.099)	(0.075)	(0.124)	(0.074)	
(UberPresent ×	0.123	0.124	0.124	0.124	0.192
BIPOC)	(0.110)	(0.114)	(0.119)	(0.113)	(0.231)
City FE	No	Yes	No	Yes	Yes
Year FE	No	No	Yes	Yes	No
BIPOC-by-year FE	No	No	No	No	Yes
Observations	682	682	682	682	682
R-squared	0.066	0.200	0.606	0.108	0.243

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1