Effect of Uber on Labour Market Outcomes: Evidence from Canada

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I. Introduction

All of the platforms that arrange the relationship between individuals on both the demand and the supply sides are called Peer to Peer (P2P). However, nowadays this economy has evolved to also be Business to Business (B2B), Business to Peer (B2P) and Peer to Business (P2B). It can be characterized by any two participants that exchange any kind of service or good around the world. This exchange is facilitated by a third-party digital platform for a fee. Sharing economy platforms use the intelligence systems to connect the supply of the underused skills, time and assets with the demand for the services created by those individuals, usually for a fee. There is not much difference between the sharing economy platforms and the online websites and applications (Amazon, eBay, etc.) except that the sharing economy doesn't involve trades based on the swap of proprietorship. According to Charles and Schor (2017), the sharing economy platforms give access to a big market of different underutilized assets and services in transportation, lodging, housecleaning, moving, storage, pet care, etc.

The sharing economy created non-traditional business models that interrupted all the current traditional industries. One of the common characteristics of the sharing economy platforms is that it links the buyers and the sellers through the web, making use of the amount of information that exists about the participants and some very well-programmed algorithms. The concepts of the supply and demand in economics are applied directly by the platforms through the pre-programmed algorithms. Those can affect the prices paid by the buyers based on the amount of services available and the demand for it.

One of the biggest platforms of the sharing economy is Uber. This is a ride-sharing service whereby the owner of a car offers a similar service to a taxi for a rider who requests a ride through the platform. The two are matched through the Uber technology, where the client requests a ride, and the closest driver who accepts to offer the service. The location of each of the participants is determined by the GPS on their mobile phones. The price of the service is determined by the distance covered, the type of service offered and, importantly, the demand and supply at the time of the request. For example, if the quantity demanded for ride sharing service were higher than the quantity supplied, the price would surge.

Sharing economy platforms in general have taken over the traditional service and goods economy affecting all its cornerstones, especially the labour market with the help of modern information and communication technologies. De Groen and Maselli (2016) reported that 44% of the population in the United States are active in the sharing economy. Also, Statistics Canada estimated that 9.5% of Canadians used ride sharing or private accommodation services. All of the workers involved in providing the services are considered in what is called the Online Labour Market (OLM) (Codagnone, Abadie and Biagi 2016). The question here is about how platforms like Uber would affect the labour market.

The labour market participants can be affected through outcomes related to employment, wages and hours worked. First, Uber opened new opportunities for the unemployed who are actively searching for a job. An unemployed individual has the opportunity to enter the labour market through operating his/her underused car, time and driving skills. Also, Uber gave a chance for employed individuals, some of which were under-employed, to moonlight as a self-employed. This is all considered as a money on the side earned in the free time while being a full-time employee. De Groen and Maselli (2016) calculated that almost 63% of the sharing economy participants are motivated by the fact that this is a second source of self-employment income. Uber can have an effect where employees would add to their hours worked through operating an Uber service. Hall and Krueger (2018) found that 61% of the Uber drivers surveyed in the U.S held another full time or part time job. The flexible schedule of working with Uber provides an incentive to get away from the hectic daily work schedule to work independently. Moreover, Uber would force the companies who employ low skilled workers to raise the wages of the low paid individuals and keep hold of employees. Li et al. (2018) found evidence of shortage in labour supply for low-skilled workers and consequently a higher wage rate for such workers in the traditional taxi industries in the United States.

In this paper I study the effect of the entrance of Uber on the labour market outcomes in Canadian Metropolitan Areas (CMAs). Uber is one of the biggest platforms, and there exist a clear entry dates into Canadian markets. The analysis concentrates on the effect of Uber on the unemployment rate, wages and hours worked by low skilled employees in Canada. The study employs monthly data from CANSIM tables and the Labour Force Survey for the period between 2010 and 2018. It utilizes the difference-in-difference method making use of the clear entry dates of Uber into different CMAs in Canada.

I find that Uber has a negative effect on the unemployment rate, decreased the unemployment, and have also a positive effect on the wages of low-skilled employees. I find no effect on usual hours worked by low-skilled employees, which suggests that employees are not substituting their regular jobs for Uber work.

II. Literature Review

The emergence of the sharing economy platforms in 2008 caught the eye of many researchers, politicians, journalists and lawyers. They all wrote about the importance and challenges imposed by the evolving sharing economy platforms. However, there are few studies analyzing the labour market outcomes of the sharing economy. Studying the effect of the sharing economy on the labour market was faced with many challenges; one of them is the lack and limitations of data about the participants of the sharing economy. It took Statistics Canada until November 2015 to start asking LFS participants about their usage of the ridesharing and accommodations platforms.[1] Most of the literature about the sharing economy is done based on the U.S. market.

Li et al. (2018) study the impact of the sharing economy platforms on the U.S. labor market. They use labor participation and unemployment rate data from the Local Area Unemployment Statistics (LAUS) program and from the Occupational Employment Statistics (OES). The authors use the Difference-in-Difference method to examine whether unemployment and wages are significantly different among metropolitan areas before and after the Uber entry date. They find that Uber significantly decreases the unemployment rate and increases the labour force participation rate. They also find a positive effect of Uber on the wages of low skilled workers.

Hall and Krueger (2018) analyze the labor market for Uber drivers in the United States. They employ the Benenson Strategy Group (BSG) survey that sampled Uber drivers in December 2014 and November 2015. They find that Uber drivers are more similar in terms of their age and education to the labor force population than to the taxi drivers' population. They also estimate that most of the drivers are full-time or part-time employees along with moonlighting as an Uber driver.

Berger et al. (2018) examine the effect of Uber on the drivers involved in traditional taxi services. They use data from the American Community Survey (ACS) and exploit the variation of the Uber entry in to different Metropolitan areas in the U.S. The authors make use of a natural experiment by applying a triple-difference method. They include in all specifications a full set of MSA fixed effects, time fixed effects and time varying city characteristics. They compare the

[1] https://www150.statcan.gc.ca/n1/daily-quotidien/170228/dq170228b-eng.htm

relative changes in earnings and employment of taxi drivers relative to other transportation industries and compare how these differences evolved pre and post Uber. They find that employment among payroll taxi drivers expanded with the Uber introduction along with an increase in the number of self-employed in the taxi industry. They also find evidence of an expansion in wage-employed taxi drivers by 10 percent along with an increase in self-employment by 50 percent. They concluded that many non-taxi drivers have become self-employed Uber drivers. The authors also find that wage-employed drivers experienced declining earnings after Uber entry, which was offset by increases in hourly wages for self-employed taxi drivers.

Zoepf et al. (2018) study the economics of ride sharing drivers especially Uber and Lyft in terms of their revenue, expenses and taxes. They use a survey of more than 1,100 drivers with detailed information about the vehicle costs and income. They find that 74% of the drivers earn less than the minimum wage in their state. They also estimate that 30% of the drivers are losing money once they include their vehicle expenses. There is also evidence that an annual $4.8B in ride sharing profit is untaxed by the U.S. government.

My paper is the only one among the recognized literature that uses a Canadian data set in studying the effect Uber on the labour market outcomes. The closest study to my paper is the one by Li et al. (2018), which deals with American labour market outcomes. We both use the difference-in-difference method exploiting the variation of the entry dates of Uber into Metropolitan Area in the U.S. and Canada. My paper focuses on methodological issues faced by using the difference-in-difference method, unlike Li et al. (2018). For instance, I test for the parallel trends assumption and tabulate the results of the test. I also test the robustness of my results through variations in regressions. Li et al. (2018) use Google trends numbers as a proxy for Uber popularity in different Metropolitan Areas in an attempt to check for the robustness of the Uber entry variable. I do not check the robustness of the Uber variable because I think that using Google Trends is not an accurate representation of the Uber effect. At some point in time, people can search for Uber on Google for the sake of curiosity or if they want a ride and not to be a driver.

III. Conceptual Framework

The sharing economy platforms implement and appeal to some major economic theories to determine prices and fees of their services. They also naturally apply a lot of other labour economics theories that let us wonder if it can be verified empirically.

For example, Uber uses the law of demand and supply to determine the prices of the rides at different times of the day. It is implemented through algorithms imbedded in the Uber app. Whenever the quantity demanded for rides exceeds the quantity supplied of drivers, the price increases marginally. This is why at some busy points of the day; Uber applies higher prices to the ride fares (Chen, et al. 2017).

I study the effect of the introduction of the Uber platform on the unemployment rate. I believe that Uber will increase the number of self-employed people and open new work opportunities, which will decrease the unemployment rate in any city it enters. A new technological innovation will lead to the provision of taxi rides in a more efficient way. Cramer and Krueger (2016) find that UberX drivers could charge 28% less in ride fares and still make the same amount of revenue per hour as a traditional taxi driver due to the efficient matching of drivers and riders through the Uber system. They also conclude that Uber is using their labor more effectively than taxis because of the technology. In most cities, there are more Uber drivers than taxis on the road, which makes it more likely for an Uber driver to be close to a potential rider than a taxi. According to the authors, this is a result of network efficiencies from scale. Due to all efficiencies in the Uber industry, the theory predicts that employment is supposed to increase, and as a result, the unemployment rate should decrease in which ever cities Uber enters. This new increase in earnings opportunity is an incentive for more people to work in relation to the prediction of the neoclassical model of labour supply (Katz and Krueger 2017).

The second part of the analysis is the fact that Uber work is attractive, with a flexible work schedule (Hall and Krueger 2018). These advantages may attract individuals with low paying jobs to switch their jobs, and as a result causing the labour supply to drop. In order to recruit and retain labour, companies that offer low-skill jobs need to raise wages. This can be related in theory to the competitive models (e.g. rent-sharing models, efficiency wage models, effort bargaining models) that predict wages will decrease in more competitive markets (Blanchflower and Machin 1996). This prediction is the opposite of the hypothesis of the more competition the higher the wages. A lot of research found evidence that there is a positive correlation between competition and wages (Slichter 1950). I base my hypothesis on the counter competition theory suggested by Slichter (1950).

The third part of the study is the hypothesis that low-skilled employees will substitute their work hours in a regular 9-5 job with Uber driving hours. I assume that employees will take the easy way to reach their income goals through self-employed work rather than a regular job.[2] The rise of alternative-income generating jobs was an incentive to individuals to substitute the regular work hours with the new work hours and take advantage of the flexible schedules (Katz and Krueger 2017). This is related to low skilled workers as they can still achieve a certain income

[2] They will take the easy way in the sense of making money with a flexible schedule instead of a 9 to 5 job.

goal while decreasing their regular job work hours (Hall and Krueger 2018). In this case, income effect for Uber drivers would be dominating the substitution effect.

IV. Data

I use unemployment monthly data from CANSIM tables accessed through Statistics Canada's website and the Labour Force Survey (LFS) to study the effect of Uber on the unemployment rate at the CMA level, hourly wages and hours worked at the individual level in Canadian Metropolitan Areas. The collected monthly unemployment data from CANSIM tables is used to study the unemployment rates in CMAs, and the LFS is utilized to study wages and hours worked.

Statistics Canada produces monthly and annual estimates on the labour market outcomes of each CMA, province and city including unemployment, population, employment, CPI, labour force, and minimum wage. I use monthly, seasonally adjusted panel data at the CMA level, June 2010 to June 2018, given that the earliest entry of Uber into Canada was in September 2014 through the cities of Toronto and Oshawa. The entry dates of Uber into various CMAs in Canada happened at different points in time, which makes it harder to balance the pre- and post-Uber time periods. I collect the data taking into consideration all the CMAs having at least few months of pre and post Uber data.[3] I also collect unemployment data of CMAs that Uber has never entered, to compare to the treated ones. The entry dates of Uber are collected from major media outlets and from the Uber website.[4] The Uber entry includes the start date of any of its services (UberX, UberBlack, UberXL and UberSUV) in any of the CMAs. Table 1 shows the Uber entry date to each CMA, and the Uber

[3] The most recent entry date of Uber is into the city of Winnipeg, Manitoba on March 1st 2018. All other cities have at least a year of post-Uber monthly data.
[4] https://www.uber.com/en-CA/cities/

services offered in each city. I have data for 34 CMAs in Canada, 17 of which have access to Uber as of June 2018, and 12 of the cities are in Ontario.[5] The number of observations is 3,298, which includes 98 months of data for each CMA. There are no cities in Nova Scotia, British Columbia, Saskatchewan, New Brunswick, Newfoundland and Prince Edward Island that host Uber.[6] Toronto on September 2014 had a population of 5,034,900. Figure 1 shows a graph of the population of each city in the month Uber kicked into it. Although Uber started with a big city, it also started serving other small cities before entering into high population areas. Therefore, we can see that Uber did not intend to enter in to cities with high population before the ones with low population. Uber entered into Kingston three years before serving Winnipeg, although Winnipeg's population is more than double of Kingston. This shows that there is no apparent correlation between Uber's decision to enter a market and its population.

The limitations of the data that it doesn't have monthly information per CMA about GDP, number of employment centers, number of schools, average education, etc. I don't restrict the sample of CMAs used to study unemployment. I use the full data set of CMAs as they are all relevant to this part of the analysis.

The second data source used to study wages and hours worked is the Labour Force Survey (LFS) from August 2010 to September 2018. The LFS provides data for the variables related to the Canadian labour market. It mainly presents data on the three categories of the working age population - employed, unemployed and not in labour force-that is usually used by government entities in the evaluation and design of different employment related programs. The Labour Statistics division interviews about 56,000 households, which

[5] There are cities where there was interruption in the Uber service but I couldn't find the date of this stoppage.
[6] The app only works based on the location of its user.

results in the collection of information for approximately 100,000 individuals each month. I appended 99 months of the LFS data resulting in a repeated cross section data set that includes 11,107,519 individuals with information on wages, education, employment status, demographics, industry and job tenure, etc. I mainly use the wage and hours worked data about individuals in the LFS along with data about their characteristics to study the effect of Uber on the variables above.

One major limitation of the public use LFS is that it only gives residency information of individuals living in Toronto, Montreal and Vancouver. All other individuals living outside the above three CMAs are put into the "Other CMA or Non-CMA" category. Statistics Canada added 6 other CMA codes in January 2017, but this change was not enough for the purpose of my study because it is after the first entry date of Uber into Canada. So, I only use data about individuals from the above 3 CMAs because the residency information of individuals from outside the above cities is not clear. Another limitation of LFS is that it collects pay and hours worked for employees only, excluding the self-employed individuals. Uber drivers are considered to be self-employed and a study that focuses on the labour market outcomes of the self-employed industry would give economically valuable results for researchers and policy makers.

I apply the same restrictions to study both the hourly wage and the hours worked. I restrict the sample from the LFS to individuals who live in the cities of Toronto, Montreal and Vancouver. Uber entered into Toronto and Montreal around the same time, while Vancouver has never had Uber serving in its city for the whole time period examined. I also restrict the sample to individual's aged 21 and over, as it is one of the requirements to be an Uber driver in the above-mentioned cities. For the purposes of my study, I remove all individuals who have educational attainment that is equal to a university or college degree or higher because I am trying to retain only the low-skilled employees. Moreover, I remove all unemployed, self-employed and not in labour force individuals because they do not have any wage information in LFS. The number of observations drops to 241,180 individuals.

Table 2 presents summary statistics of the restricted sample from LFS. We can see that 48% of our sample is in Toronto compared to 30% in Montreal and 22% in Vancouver. The share percentage of females is 46.2% and the share of singles is 40.7%. Among the three low education categories, 56.6% have graduated from high school and 22.3% have some post-secondary education. Moreover, Table 2 presents some statistics pre and post first Uber entry date to Canada. Most individuals are aged 20 to 24 after the Uber entry, and it is the same for the pre-Uber. The average wage is $18.86 pre-Uber, while it increases to $20.09 post Uber.[7] The proportion of treated individuals post-Uber is 75.3%. The percentage of individuals holding a high school diploma is 60%, while it was 53% before the Uber entry. The fraction of individuals holding multiple jobs stayed the same pre and post Uber (3.8% vs 3.9%). The average number of tenure months is 87 months before the Uber entry and drops to 78 months after it.

V. Methodology

I explore the effect of Uber on the unemployment rate in CMAs, hours worked and wages of the low skilled employees in Canada. This choice of outcomes is based on three factors. For unemployment, the emergence of what is usually called the new economy, which is characterized by the sharing economy platforms, have opened new informal employment

[7] Average hourly wages are adjusted for inflation with 2014 as the base year.

opportunities for the jobless individuals who are still in the labour force (National Training Fund 2017). I also believe that the sharing economy created a wage substitution effect that forced businesses that hire low-skilled workers to increase the wages in order to attract workers away from the sharing economy (Li, Hong and Zhongju 2018). Also, the low-skilled workers in the presence of Uber and its counterparts could be more tempted to work fewer hours in a formal job and add the extra hours into doing tasks in the sharing economy (Nurvala 2015).

I use the event of Uber entry to estimate its effect on the labour market outcomes, as it represents two thirds of the labour activity happening in the platform economy according to Harris and Krueger (2015). I examine the effect of Uber on various labour outcomes exploiting the variation caused by the different entry dates of Uber into various Canadian cities. My concern is that the decision of Uber entry into a city is endogenous and there might be a correlation between city or individual characteristics and the decision of Uber to enter. Uber may decide to enter into a city based on the population. Figure 1 represents a bar graph of each CMA population at the date of Uber entry. We can see that Uber entered into Calgary a year after Ottawa although the population of Calgary (1.2 million) is higher than the one in Ottawa (0.8 million) in the month Uber entered into each city. Uber entered to some cities that have less population on an earlier date than the one with high population. Another endogeneity problem is the Uber decision to enter based on the average income of the city. We can see that Uber entered first Toronto (September, 2014) and then into Calgary (October, 2015). Calgary had a higher metropolitan average income than Toronto in 2014, but Uber did not enter into it first.[8] Moreover, although Vancouver had a higher average income than Montreal in 2014, Uber has never entered it. This could be due to the opposition of the Vancouver city council and the BC MPPs to the ride hailing service.[9] The opposition of the city officials is another reason that affects Uber's decision to enter a market. An example that I believe it also affects Uber's decision to enter a city is what happened in Innisfil, Ontario where the city found that Uber is a more affordable solution as a public transit.[10] They also found that they could save $8M per year by partnering with Uber for public transit. This is a factor that is correlated with the Uber decision to enter Innisfil. In terms of individual characteristics in the LFS, there might be correlation between them and Uber's decision to enter a certain city. Hall et al. (2018) predicted that the population and education in a city are highly correlated with whether Uber enters a metropolitan area. All of these factors suggest threat to the identification of the model.

The labour market outcomes are changing significantly over time in Canada (Hardy, Lovei and Patterson 2018). There are other factors that might be driving the labour market outcomes other than the Uber effect. We need to answer the following question: what would have been the change in unemployment, wages and hours worked had there been no Uber entry into any of the cities? The difference between the change that happened in the treatment group and the change in the counterfactual group would be the effect of Uber. This is conditional on the assumption that the control group is comparable.

One way to approach this is to form a comparable group of cities and individuals that have never been treated by Uber. For the unemployment outcome, the treatment group are

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[8] https://www150.statcan.gc.ca/t1/tbl1/en/cv.action?pid=1110023701
[9] https://bc.ctvnews.ca/vancouver-the-only-nhl-city-without-ride-hailing-canucks-owner-vents-1.4109013
[10] https://www.uber.com/cities/innisfil/partnership/

the CMAs that Uber has entered. I choose the control group as all the CMAs that Uber has not entered yet as of June 2018. This is the most comparable group as all those cities are in Canada. The average unemployment rate for the treatment group pre-Uber is 7% which is close to the one for the control group at 6.6%. In examining the trends of the unemployment rates in the treatment group, I can see that the unemployment rate dropped from 7.3% to 6.8% pre-Uber between 2011 and 2013. The average unemployment rate was at 7% in 2011 for the control group, and it dropped to 6.5% in 2013. I can see that the two groups are close to each other in terms of comparability.

For the wages and hours worked analysis (using LFS), the treatment group is comprised of individuals who lived in Toronto and Montreal. Uber entered the city of Toronto on September 2014 and the city of Montreal on October 2014. At the time of writing of this paper, Uber has never worked in Vancouver. I choose the individuals who live in Vancouver as the control group. I can then compare the change in wages or work hours of the treatment group to the control groups as a way to estimate the Uber effect on these outcomes. The average hourly wage for the treatment group before Uber is 18$, which is somewhat lower than the average wage of the control group at 20$. The proportion of individuals holding a high school degree is 52% for the treatment group, while it is 59% for the control group. The average current job tenure is 78 months for the treatment group, while it is 80 months for the control group pre-Uber. Moreover, the average number of hours worked is 33 hours for individuals in the treatment group and 34 hours in the control group. The hourly wage for low skilled workers in the treatment group increased slightly on average per year from 18$ in 2011 to 18.2$ in 2013. The hourly wage for the control group increased from 19.2$ on average in 2011 to 20$ in 2013. For our second outcome, the hours worked was 33.1 hours in 2011 for the treatment group, which decreased to 32.7 hours in 2013. In the control group, individuals worked on average 32.8 hours per week at their main jobs, and it stayed almost the same going to the year 2013.

The comparison above between the treatment groups and the control groups shows that they are close enough in terms of some characteristics and trends of the labour outcomes.

The most important identifying assumption in applying the difference-in-difference is the parallel trends assumption. This states that if Uber had not been in operation, the unemployment rate, wages and hours worked of the treated cities would have changed by the exact amount as the ones in the counterfactual group. This is the parallel trends assumption and it could also be violated. One would argue that Vancouver (the control group) is more vulnerable to macroeconomic shocks than Montreal because of its volatile housing market and as a result it can get a higher unemployment rate at some periods of time. I statistically test the parallel trends assumption through the leads and lags test in the results section (Granger 1969).

I use the following specification to study the effect of Uber on the unemployment rate. The specification is:

$$UNEMPLOYMENT_{ct} = \beta_0 + \beta_1 \, UBER_{ct} + \gamma X_{ct} + \theta_c + \gamma_t + \varepsilon_{ct} \qquad (1)$$

where the dependent variable is the unemployment rate in CMA c in the month t. $UBER_{ct}$ is a dummy variable equal to 1 whenever Uber is present in a CMA and 0 otherwise. X_{ct} is a group of control variables such as the population of each CMA per month, θ_c is a CMA fixed effects to control for any time-invariant differences between the areas, and γ_t is a month fixed effects to control for any time shocks that is common to all groups. Our variable of interest is β_1.

The wages and hours worked are specified by:

$$Logwage_{ict} = \alpha_0 + \alpha_1 UBER_{ict} + \gamma X_{ict} + \theta_c + \gamma_t + \varepsilon_{ict} \qquad (2)$$

$$hours_{ict} = \delta_0 + \delta_1 UBER_{ict} + \gamma X_{ict} + \theta_c + \gamma_t + \varepsilon_{ict} \qquad (3)$$

Where $Logwage_{ict}$ is the log of the hourly wage of individual i living in CMA c in month t, and $hours_{ict}$ is the number of usual hours worked in the main job by individual i living in CMA c in month t. $UBER_{ict}$ is equal to one if the individual lives in an Uber city at the time of the post entry date of Uber. X_{ict} is a group of covariates such as the age, education, and province. I also added city and month fixed effects but not individual effects because the data used here is a repeated cross section.

VI. Results

A. Unemployment

Initial estimates of equation (1) are presented in table 3. Each column presents a regression of the unemployment rate on CMA and month dummies, CMA specific time trends, population and an indicator variable of Uber which is equal to one if it is present in a given CMA and month and zero otherwise. The first two columns contain the estimated effect of Uber on the unemployment rate. The estimate of -0.875 in column 1 indicates that without controlling for population, time trends, month and CMA fixed effects, the unemployment rate decreases by 0.875 percentage points more in the CMAs that have Uber than in the ones that do not. The second column adds CMA specific time trends to the model, the estimated effect increases to -0.668. This means that Uber decreased unemployment rate by 0.668 percent in Uber areas relative to non-Uber ones. In both cases, the estimates are significant at the 5 percent level.

In column 3, I add the CMA population to the model. The estimated effect of Uber increases to -0.862, which means that the unemployment rate in Uber areas is 0.862 percent lower than the non-Uber ones, all other factors constant. The estimate remains significant at the 5 percent level. Column 4 includes the full specification including the variables of population, CMA fixed effects, monthly fixed effects and CMA specific time trends. The estimated Uber effect drops to -0.654 percentage points. The estimate in column 4 is now significant at 10% level.

Column 5 estimates the effect of Uber with only CMA and month fixed effects. The estimated effect increases back to -0.881, which means that the unemployment rate in Uber areas is 0.881 percentage points lower than in non-Uber CMAs. The estimate is significant at the 5 percent level. Column 6 keeps the same specification as the one in Column 5 but adds the CMA specific time trends. Nothing changes with the addition of the time trends.

Column 7 includes population, the CMA and month fixed effects. The estimated effect is at -0.654 again, which means that the unemployment rate in the Uber CMAs is 0.654 percentage points lower than in the non-Uber CMAs. The estimate is statistically significant at the 5% level.

Although the F tests for the joint relevance of the CMA specific time trends show statistical significance, adding it to any of specifications above didn't change any of the results, and the Uber estimate is largely insensitive to the addition of those trends.

The above specifications provide no idea of the dynamics of the unemployment rate before and after Uber. The questions asked here are: How quickly the unemployment rate decreased after Uber entered for the first time the regions in Canada? Does the effect grow or fade out with time? Do the changes in the unemployment rate of the treatment and control groups pre-Uber follow a parallel trend? To answer those questions, I estimate the equation 1 augmented with leads and lags interaction terms.

Table 4 shows the results of the leads and lags specifications five months before and after the first Uber entry into Canada. The effect of Uber starts in September, 2014 with its entry into Toronto. The effect of Uber is small and not significant in some periods of time before Uber. It becomes significant in few months and not significant in others. The estimate ranges between -1.10 and -1.26 percentage points pre-Uber and a lot of those point estimates are statistically significant at the 1% level. This is an evidence of violation of the parallel trend assumption. It suggests that there are factors other than Uber affecting the unemployment rate.

Also, I did an F test of the hypothesis that all the lead factors are equal to zero under three different specifications, as shown in table 4. I reject the null hypothesis in all three cases, and statistically this gives me evidence that the parallel trend assumption fails. This suggests that the entry of Uber is endogenous. There are other factors that affect the labour market outcomes and is also correlated with the treatment. The estimates are increasing with time post Uber, as shown in table 4. They increase from -1.233% in the month Uber entered to high -1.705% just 3 months after. This is a signal that the effect is accumulative with time. Uber enters into a city and the city council legalizes it after some time. Uber illegally operated in Ottawa since October 2014 and the City of Ottawa passed a new taxi bylaw for ride sharing services that went into effect on September 2016. The effect of Uber on unemployment increases more when it becomes legal, as more people will feel safe to join it.

Uber had some effect due to the opening of the app to some cities before officially launching it in Toronto. [11]Moreover, Uber was evicted by the city after its launch because of the risk associated with its services. Regulators in Gatineau forced Uber to cease operations after they launched in the city in 2014.[12] Uber has also been threatening all the time to exit Quebec. The Province of Quebec and the Montreal Taxi Bureau were fighting them, which is another factor contributing to the endogeneity of the treatment.[13]

B. Low Skilled Wages and Hours Worked

I show the results of the low-skilled wages and of hours worked in Table 5. It presents estimates from equation 2 using observations from Vancouver as a control group. First, I include only the treatment dummy and the time fixed effects. The effect of Uber entry increased wages of the low-skilled employees in Toronto and Montreal by 7.9 %relative to those paid in Vancouver. The estimate is significant at the 1% level. The time fixed effects for all months of the year are very small in magnitude and insignificant. In column 2, I add several demographic controls such as the province dummies, age and marital status. The estimate drops to 0.064, which means that wages of the low skilled workers were 6.4 % higher in Uber CMAs more than they were in Vancouver. Ontario and Vancouver have a higher wage levels compared to Quebec.

In column 3, I add the education dummies. The estimate in this case is at 0.063, indicating that wages are 6.3% higher in Toronto and Montreal than in Vancouver after the Uber entry. A reasonable result here is that low-education individuals earn 20.4 % less in wages than people with some post-secondary education. The number decreases in magnitude as

[11] https://www.itbusiness.ca/news/uber-launches-taxi-app-in-toronto/18187
[12] https://www.cbc.ca/news/canada/ottawa/uber-drivers-not-welcome-in-gatineau-either-says-regulator-1.2794058
[13] https://globalnews.ca/news/3769417/a-look-at-ubers-controversial-history-in-quebec/

the individuals obtain more education; it is 10.8% less in the case of some high school education. This result aligns with the results from literature about the effect of education on wages. Forbes et. al (2010) find that a high school degree holder earns 13 % higher in wages than a person with year 11 education or less.

In column 4, I include only Uber as a treatment dummy and the education dummies. The estimate increases to 0.076 with a 1% significance level. In column 5, I try adding the monthly fixed effects to the regression used in column 4, and the results do not change. In column 6, I add CMA specific time trends to the regression whose results are listed in column 3. The addition of time trends did not change the Uber estimate and it remains at 0.065. The estimates of the CMA specific time trends are negligible although significant at the 1 % level. I leave out the time trends in my specifications, as the results are insensitive to it.

Considering my preferred specification in column 3, the sign of the estimate on Uber aligns with my expectations from theory. I expected that Uber would reinforce competition in the labour market for the businesses that employ low-skilled labour, which will increase wages on average. Uber will lure workers away from low paying jobs and this would force businesses to increase average wages in order to retain them. In other words, businesses that pay low wages increased on average the wages they pay in order to face the competition offered by Uber.

Table 6 presents the results for hours worked. I use here the usual hours worked by an employee as the dependent variable. Column 1 shows the estimates of the regression that includes the treatment variable and the monthly fixed effects. The estimated coefficient of Uber is 1.551, which means that usual hours worked in Uber CMAs is 1.55 hours more than in the non-Uber cities as a result of the Uber entry, all other factors held constant. Column 2 includes the specification with all the demographic and education controls. The estimated sign changes to negative and drops to -0.315. The effect of Uber on the hours worked in this case is negligible. Also, a remarkable result here is that employees with low education, work usually 2.675 more hours than people with some post-secondary education. Column 3 shows the same above regression but with the addition of the monthly fixed effects. The results did not change in general however I obtained a statistically insignificant estimate for the coefficient of Uber.

Although I expected that individuals would substitute their time at a formal 8-hour shift job with more hours at a flexible schedule with Uber, the change in the number of usual hours worked due to Uber is economically insignificant which is opposite to the expectation. A justification of this would be that employees are moonlighting as Uber drivers. This makes it complement and not a substitute of a regular work hours in a full time or part time job. Although Berger et al. (2018) states that most of the Uber drivers are transitioning out of full time and part time jobs but our results indicate they are taking it as a money on the side.

VII. Robustness checks

In addition to the parallel trends assumption check done before, I further assess the plausibility of the identifying assumption by changing the treatment groups. I remove all individuals in Montreal from the treatment group and I compare wages and hours worked in Toronto to the ones in Vancouver only. The entry of Uber into Toronto was permanent with no stoppage in the service since it started there. The Uber start in Montreal was a little bumpy, with Uber threatening to exit the city several times.[14] I choose to exclude individuals from Montreal from the treatment group in this robustness check. I find that my results are robust to changes in the comparison groups. All the estimates are close to the ones I obtained before when including individuals from Montreal in the treatment group. The estimated coefficient of the Uber variable from our different specifications in columns 1 to 5 are almost 0.05, which means that individuals in Toronto have on average 5% higher in wages than workers in Vancouver after the Uber entry, all other factors held constant. This result is on average close in magnitude to the one that includes Montreal in the treatment group. The results are all statistically significant at the 1% level. Table 8 shows the different estimates for the hours worked regressions. Columns 2 and 3 show the negligible effect of Uber on hours worked by employees in Toronto, which is the same as when I included Montreal in the treatment group. However, the sign on the estimates turned from negative to positive. The results are not robust to the changes I made to the treatment groups.

Another robustness check I did was on the unemployment data. I estimate equation (1) excluding the year 2014. I do this for two reasons. The first is that Uber entered Canada for the first time in September 2014. I assume the effect of Uber on unemployment was not strong in the months after the first entry of Uber. The second reason is that Uber might have done some testing to the Canadian market before officially entering it, and this will make it unclear to say that the year 2014 is a pre or post year. Table 9 shows the estimates from equation (1). The effect of Uber on unemployment rate is approximately the same and did not change even with the year 2014 still included. Column 4 in table 9 includes the results from the regression of unemployment including all our control variables, fixed effects and time trends. The

[14] They actually seized operations in Montreal in 2014 and 2015 but I was not able to find the exact date and duration of this stoppage.

unemployment rate is 9.3% lower in Uber CMAs than in the non-Uber ones when eliminating the year 2014. This result is not really close to the one that included the data from the year 2014 (6.5%). All other columns present the results of the regressions that eliminates the controls, fixed effects and the time trends. The Uber effect ranges 1% to 2% away from the past estimates that included the year 2014. This indicates that our results are not very robust to removing any data related to an uncertain year of the entry for Uber.

VIII. Conclusion

The analysis of the effect of Uber on the labour market outcomes allows me to arrive at some conclusions. I find a negative relationship between the entry of Uber and unemployment rate in each CMA. The unemployment rate was 6.5 and 8.8 percentage points lower in Uber CMAs than in the non-Uber ones. I also find a positive relationship between Uber and the wages of the low-skilled, earning them 6.3% to 8% higher wages if they live in an Uber CMA. I also find a negligible effect of Uber on the worked hours by the low skilled employees. Except for the effect of Uber on the worked hours hypothesis, my results are in line with my expectations that are derived from economic theory. Uber has and will negatively affect unemployment. It will create jobs and also be an opportunity for workers to have a second income. It will also act as a competitor to businesses that employ low-skilled workers and require them to raise wages to retain labour supply. We can only understand this new economy by continuous studies in labour economics. Every year, new data will become available, and it remains for researchers and governments to utilize data and understand the labour market outcomes of the sharing economy.

IX. References

Beck, Nathaniel, and Jonathan N. Katz (1995) 'What to do (and not to do) with Time-Series Cross-Section Data.' *The American Political Science Review* 89 (3): 634-647

Berger, Thor, Carl Frey, Guy Levin, and Santosh Danda (2018) 'Uber Happy? Work and Wellbeing in the "Gig Economy". ' Working paper, London: *68th Panel Meeting of Economic Policy*

Berger, Thor, Chinchih Chen, and Carl Benedikt Frey (2018) 'Drivers of Disruption? Estimating the Uber Effect.' *European Economic Review* 197–210

Blanchflower, David, and Stephen Machin (1996) 'Product Market Competition Wages and Productivity: International Evidence from Establishment-Level Data. ' *Annales d'Économie et de Statistique* (JSTOR) 219-253

Charles, William Attwood, and Juliet Schor (2017) 'The "sharing" economy: labor, inequality, and social connection on for-profit platforms.' *Wiley* 1-16

Chen, M. K., J. A. Chevalier, P. E Rossi, and E. Oehlsen. (2017) 'The Value of Flexible Work: Evidence from Uber Drivers.' NBER Working Papers No. 23296

Codagnone, Cristiano, Fabienne Abadie, and Federico Biagi (2016) 'The Future of Work in the 'Sharing Economy'. Market Efficiency and Equitable Opportunities or Unfair Precarisation? . ' *JRC Science for Policy Report*, EUR: Institute for Prospective Technological Studies

Cramer, Judd, and Alan B. Krueger (2016) 'Disruptive Change in the Taxi Business: The Case of Uber.' *American Economic Review* 106 (5): 177-182

De Groen, Willem Pieter, and Ilaria Maselli (2016) 'The Impact of the Collaborative Economy on the Labour Market.' Brussels: Centre for European Policy Studies

Forbes, Matthew, Andrew Barker, and Stewart Turner (2010) 'The Effects of Education and Health on Wages and Productivity. ' Working Paper, Melbourne: Australian Government Productivity Commission

Granger, C.W.J. (1969) 'Investigating Causal Relations by Econometric Models and Cross-spectral Methods.' *Econometrica* 37 (3): 424-438

Hall, Jonathan V., and Alan B. Krueger (2018) 'An Analysis of the Labor Market for Uber's Driver-Partners in ther United States.' *ILR Review* 705–732

Hardy, Vincent, Marton Lovei, and Martha Patterson (2018) 'Recent trends in Canada's labour market: A rising tide or a passing wave?' Ottawa: Statistics Canada

Harris, Seth, and Alan Krueger (2015) 'A proposal for modernizing labor laws for twenty-firstcentury work: The "independent worker" ' Discussion Paper, Washington, DC: Brookings Institution

Katz, Lawrence F., and Alan B. Krueger (2017) 'The Role of Unemployment in the Rise in Alternative Work Arrangements ' *American Economic Review* 107 (5): 388-392

Kim, Chong-Uk, and Gieyoung Lim (2018) 'Minimum Wage and Unemployment: An Empirical Study on OECD Countries ' *Journal of Reviews on Global Economics* 1-9

Li, Ziru, Yili Hong, and Zhang Zhongju (2018) 'An Empirical Analysis of the Impacts of the Sharing Economy Platforms on the U.S. Labor Market.' *Hawaii International Conference on System Sciences.* Hawaii: HICSS. 666-679

National Training Fund (2017) 'Impact of shared economy on a position of employees and proposed changes in legislation .' Prague: Association of Independent Trade Unions

Nurvala, Juha-Pekka (2015) ' 'Uberisation' Is the Future of the Digitalised Labour Market.' *SAGE journals* 14 (2): 231-239

Slichter, S. (1950) 'Notes on the Structure of Wages. ' *Review of Economics and Statistics* (32): 80-91

Smith, Adam (1776) ' An Inquiry into the Nature and Causes of the Wealth of Nations' London: W.Strahan and T.Cadell

Zoepf, Stephen, Stella Chen, Paa Adu, and Gonzalo Pozo (2018) 'The Economics of Ride-Hailing: Driver Revenue, Expenses and Taxes.' Working Paper Series, Massachusetts: MIT CEEPR

X. Figures and Tables

Table 1 Uber Entry dates to each CMA

City	Province	Start Date	Types of Uber Service
Calgary	Alberta	October 2015	UberX, UberXL, Uber Select
Edmonton	Alberta	December 2014	UberX, UberXL, UberSELECT
Hamilton	Ontario	July 2015	UberX
Kingston	Ontario	November 2015	UberX
Kitchener-Waterloo	Ontario	July 2015	UberX
Oshawa	Ontario	September 2014	UberX
London	Ontario	July 2015	UberX
Montreal	Quebec	October 2014	UberX, UberXL, UberSELECT, TAXI
Ottawa	Ontario	October 2014	UberX, UberXL, UberASSIST
Quebec City	Quebec	October 2014	UberX, UberXL
Toronto	Ontario	September 2014	UberX, UberXL, UberPOOL, UberSELECT, UberBLACK, UberSUV, UberASSIST, UberWAV, TAXI
Windsor	Ontario	November 2015	UberX
St. Catharines-Niagara	Ontario	November 2015	UberX
Brantford	Ontario	July 2015	UberX
Guelph	Ontario	July 2015	UberX
Barrie	Ontario	July 2015	UberX
Winnipeg	Manitoba	March 2018	UberX

Table 2. Summary Statistics of individuals from LFS

	Restricted Sample	Pre-Treatment	Post-Treatment
A. Wage ($)	19.5 (9.85)	18.3 (9.46)	20.8 (10.10)
B. Usual Hours Worked	33.8 (10.85)	32.9 (11.47)	34.8 (10.04)
C. *Labour Conditions*			
Full time	0. 76 (0. 42)	0. 72 (0. 44)	0. 79 (0. 40)
Single Job	0. 96 (0. 19)	0. 96 (0. 19)	0. 96 (0. 19)
Not Unionized	0. 77 (0. 41)	0. 77 (0. 41)	0. 77 (0. 41)
D. Marital Status			
Married	0. 38 (0. 48)	0. 37 (0. 48)	0. 39 (0. 48)
Common Law	0.11 (0. 32)	0.10 (0. 31)	0.12 (0. 33)
Widowed	0. 01 (0. 11)	0. 01 (0. 11)	0. 01 (0. 12)
Separated	0. 02 (0. 16)	0. 02 (0. 16)	0. 02 (0. 16)
Divorced	0. 04 (0. 21)	0. 04 (0. 21)	0. 04 (0. 21)
Single	0. 40 (0. 49)	0. 43 (0. 49)	0. 38 (0. 48)
E. Gender			
Female	0. 46 (0.49)	0. 47 (0.49)	0. 44 (0.49)
F. Age			
20-24	0. 17 (0. 37)	0. 15 (0. 36)	0. 19 (0. 39)
25-29	0. 09 (0. 28)	0. 08 (0. 27)	0. 09 (0. 29)
30-34	0. 08 (0. 27)	0. 07 (0. 26)	0. 08 (0. 27)
35-39	0. 07 (0. 26)	0. 06 (0. 25)	0. 08 (0. 27)
40-44	0. 08 (0. 27)	0. 08 (0. 27)	0. 08 (0. 27)
45-49	0. 10 (0. 30)	0. 10 (0. 30)	0. 09 (0. 29)
50-54	0. 12 (0. 32)	0. 12 (0. 32)	0. 12 (0. 33)
55-59	0. 10 (0. 30)	0. 09 (0. 28)	0. 11 (0. 32)
Over 60	0. 10 (0.25)	0. 08 (0.23)	0. 11 (0.16)
G. Education			
Low Education	0. 05 (0. 21)	0. 05 (0. 22)	0. 04 (0. 21)
Some High school	0. 16 (0. 36)	0. 18 (0. 38)	0. 13 (0. 34)
High school	0. 56 (0. 49)	0. 53 (0. 49)	0. 59 (0. 49)
Some Post-Secondary	0. 22 (0. 41)	0. 23 (0. 42)	0. 21 (0. 40)
H. Region			
British Columbia	0.21 (0.40)	0.21 (0.40)	0.21 (0.41)
Quebec	0. 30 (0.44)	0. 30 (0.45)	0. 30 (0.46)
Ontario	0. 48 (0.49)	0. 48 (0.49)	0. 47 (0.49)
Observations	241,180	134,335	106,845

Notes. All statistics are weighted. The standard errors are in brackets.

Table 3. Results of six different specifications studying unemployment rate

EXP. Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Uber	-0.87**	-0.66**	-0.86**	-0.65*	-0.88**	-0.88**	-0.65**
	(0.35)	(0.28)	(0.35)	(0.33)	(0.35)	(0.35)	(0.33)
population			-0.18	-3.9			-3.9
			(0.27)	(4.2)			(4.2)
CMA F.E.				YES	YES	YES	YES
Month F. E				YES	YES	YES	YES
CMA time trends		YES		YES		YES	
Observation	3298	3298	3298	3298	3298	3298	3298

Notes. The dependent variable is the unemployment rate. Robust standard errors are in parentheses. The estimation technique is the Ordinary Least Squares (OLS).

Table 4. Results of the Leads and Lags test using the unemployment equation

EXP. Variables	(1)	(2)	(3)
Uber	-0.15	-0.14	-0.15
	(0. 41)	(0. 41)	(0. 41)
Uber Entry t +5	- 1.2***	- 1.2***	- 1.2***
	(0.28)	(0.28)	(0.42)
Uber Entry t +4	-1.1***	-1.1***	-1.1**
	(0.27)	(0.27)	(0.42)
Uber Entry t +3	-1.1***	-1.1***	-1.1**
	(0.28)	(0.28)	(0.44)
Uber Entry t +2	-1.1***	-1.1***	-1.2**
	(0.27)	(0.27)	(0.45)
Uber Entry t +1	-1.1***	-1.1***	-1.2**
	(0.28)	(0.28)	(0.46)
Uber Entry t	-1.2***	-1.2***	-1.2**
	(0.33)	(0.33)	(0.51)
Uber Entry t-1	-1.4***	-1.4***	-1.4***
	(0.39)	(0.39)	(0.55)
Uber Entry t -2	-1.6***	-1.6***	-1.6***
	(0.39)	(0.39)	(0.55)
Uber Entry t -3	-1.7***	-1.7***	-1.7***
	(0.39)	(0.39)	(0.56)
Uber Entry t -4	-1.6***	-1.6***	-1.7***
	(0.39)	(0.39)	(0.56)
Uber Entry t -5	-1.6***	-1.6***	-1.6***
	(0.39)	(0.39)	(0.55)
CMA effects	YES		YES
Monthly Effects	YES		YES
All Controls		YES	YES
F test Uber Entry H_0-H_{51}	8.6	1568.5	10.7
Observations	3298	3298	3298

Notes. The dependent variable is the log of unemployment. I only present the estimates of the lead and lags factors 5 periods before and after the first Uber entry. I test for the significance of all pre-Uber leads with an F test. Here I use eq. 1 to see the effect of the leads and lags on unemployment rate.

Table 5. Results of six regression from the wage equation

EXP. Variables	(1)	(2)	(3)	(4)	(5)	(6)
Uber	0.07***	0.06***	0.06***	0.07***	0.07***	0.06***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Low Education			-0.20***	-0.06***	-0.06***	-0.20***
			(0.01)	(0.00)	(0.00)	(0.00)
Some High school			-0.10***	-0.06***	-0.06***	-0.10***
			(0.01)	(0.00)	(0.00)	(0.00)
High School			-0.03***	0.08***	0.08***	-0.03***
			(0.01)	(0.00)	(0.00)	(0.00)
Ontario		0.06***	0.05***			0.06***
		(0.01)	(0.01)			(0.00)
BC		0.12***	0.11***			0.08
		(0.01)	(0.00)			(0.00)
Age		YES	YES			YES
Marital Status		YES	YES			YES
Monthly Effects	YES		YES		YES	YES
CMA time trends						YES
R-squared	0.01	0.21	0.22	0.02	0.02	0.22
Observation	241,180	241,180	241,180	241,180	241,180	241,180

Notes. The dependent variable is the log of hourly wage earned. Robust standard errors are in parentheses. The estimation technique is Ordinary Least Squares (OLS).

Table 6. Results of three regressions of the number of hours worked

EXP. Variables	(1)	(2)	(3)
Uber	1.55***	-0.31***	-0.27***
	(0.04)	(0.04)	(0.00)
Low Education		2.6***	2.6***
		(0.09)	(0.09)
Some High school		1.9***	1.9***
		(0.06)	(0.06)
High School		1.8***	1.8***
		(0.05)	(0.05)
Log wage		4.4***	4.4***
		(0.53)	(0.05)
Ontario		0.35***	0.35***
		(0.04)	(0.04)
BC		-0.00	0.01
		(0.05)	(0.05)
Age		YES	YES
Marital Status		YES	YES
Monthly Effects	YES		YES
CMA time trends			
R-squared	0.01	0.27	0.28
Observation	241,180	241,180	241,180

Notes. The standard errors are robust. The dependent variable is the usual number of hours worked by a low skilled employee. Robust standard errors are in parentheses. The estimation technique is the Ordinary Least Squares (OLS).

Table 7. Results of robustness checks using data of Toronto and Montreal only

EXP. Variables	(1)	(2)	(3)	(4)	(5)
Uber	0.05***	0.04***	0.04***	0.04***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Low Education			-0.06***	-0.06***	-0.22***
			(0.00)	(0.01)	(0.01)
Some High school			-0.09***	-0.09***	-0.11***
			(0.00)	(0.00)	(0.00)
High School			0.07***	0.07***	-0.04***
			(0.00)	(0.00)	(0.00)
Ontario		-0.06***			0.02***
		(0.00)			(0.00)
Age		YES			YES
Marital Status		YES			YES
Monthly F.E	YES		YES		YES
CMA time trends					YES
R-squared	0.00	0.21	0.01	0.01	0.22
Observations	155,717	155,717	155,717	155,717	155,717

Notes. The dependent variable is the log of hourly wage. Robust standard errors are in parentheses. I restrict this sample to only individuals from Toronto and Montreal.

Table 8. Results of the robustness checks using Toronto and Montreal data only

EXP. Variables	(1)	(2)	(3)
Uber	1.60***	0.11	0.15
	(0.07)	(0.07)	(0.07)
Low Education		1.42***	1.43***
		(0.13)	(0.13)
Some High school		0.94***	0.95***
		(0.08)	(0.08)
High School		1.67***	1.68***
		(0.06)	(0.06)
Ontario		0.02	0.01
		(0.05)	(0.05)
Age		YES	YES
Marital Status		YES	YES
Monthly Effects	YES		YES
CMA time trends			
R-squared	0.00	0.25	0.25
Observations	155,717	155,717	155,717

Notes. The standard errors are robust. The dependent variable is the usual number of hours worked by an employee. Robust standard errors are in parentheses. Regressions using OLS. I restrict the sample to individuals from Toronto and Montreal.

Table 9. Results of Robustness checks excluding the year 2014

EXP. Variables	(1)	(2)	(3)	(4)	(5)
Uber	-0.97***	-0.98**	-0.93**	-0.93**	-0.98**
	(0.37)	(0.37)	(0.36)	(0.36)	(0.37)
population			0.00	0.00***	
			(0.00)	(0.00)	
CMA F.E.		YES	YES	YES	YES
Monthly F.E.			YES	YES	YES
CMA time trends		YES		YES	
Observations	2890	2890	2890	2890	2890

Notes. The standard errors are robust. The dependent variable is the unemployment rate. Robust standard errors are in parentheses. I use OLS in all regressions.

Figure 1. Population of each CMA at the Uber entry date