Gig Economy and Ethnic Minorities Self-Employment

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Abstract (English)

In this dissertation titled ”Gig Economy and Ethnic Minorities Self-Employment, I, Lilie Timricht, investigate the impact of the development of gig work platforms on the creation of new self-employed activities in the ride-hailing sector, and on the participation of ethnic minorities, leveraging the rollout treatment of UberX platform in France. Results from an event study design approach reveal that the platform significantly raised the number of new self-employed drivers registrations, and increased the share of drivers with African ethnic background by around 10 percentage points. These results suggest that the gig economy created new pathways to self-employment, especially for ethnic minorities.

Keywords: Gig economy, self-employment, ethnic minorities, Uber, event study.

Abstract (Portuguese)

Nesta dissertação, intitulada *“Gig Economy and Ethnic Minorities Self-Employment,”* eu, Lilie Timricht, investigo o impacto do desenvolvimento de plataformas de trabalho “gig” na criação de novas actividades por conta própria no sector dos serviços de transporte de passageiros e na participação de minorias étnicas, tirando partido do tratamento de lançamento da plataforma UberX em França. Os resultados de uma abordagem de estudo de eventos revelam que a plataforma aumentou significativamente o número de registos de novos condutores independentes e aumentou a percentagem de condutores de origem étnica africana em cerca de 10 pontos percentuais. Estes resultados sugerem que a economia gig criou novas vias para o trabalho independente, especialmente para as minorias étnicas.

Palavras-chave: Economia gig, trabalho por conta própria, minorias étnicas, Uber, estudo de eventos.

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Contents

1 Introduction

Migrants and ethnic minorities are typically confronted with higher unemployment rates and face greater barriers to stable employment than the native population : in 2008 in France, while the unemployment rate was 4.6% for natives, almost 11.5% and 14.1% of first and second generation immigrants from non-European countries were unemployed (Gorodzeisky et al. 2017). In recent years, the emergence of digital labour platforms introduced a new form of self-employment where services are provided on demand. Platforms such as Uber have significantly lowered the costs associated with the development of an independent activity, potentially offering easier access to income generating opportunities. In this context, the rise of platform work raises important questions about its implications on employment access inequalities. In this paper, I answer the following question : does online platform work expand self-employment more for ethnic minorities than for others in France ?

To address this question, I construct an original dataset that combines administrative records on newly registered self-employed businesses in France, with estimates on ethnic origin inferred from individuals' names using an algorithm. The final dataset provides annual information on both the number and the ethnic composition of new self-employed drivers across French cities.

I use this dataset to estimate the effect of Uber's entry on the ethnic composition of new self-employed drivers and implement an event study design covering the period 2009 - 2019. Treated cities are those where Uber enters during the observation window, while the control group consists of the cities where Uber either never enters, or only does so after 2019 ("never-treated" group). To limit spillover effects that could bias the estimated impact downward, the control group is restricted to cities located outside a 30-kilometre radius of the treated cities.

I find that the entry of the UberX platform in a city leads to an increase in the number of new registered drivers, and a rise in the share of drivers with an African ethnic background. While the ethnic composition does not seem to be affected in the immediate years after Uber's entry, the estimates show a significant increase of around 15 percentage points in the share of African-background drivers around three years after treatment. To address potential composition effects, the event study is estimated separately on different treatment cohorts : first for cities treated in the 2013 - 2014 period (large cities initially targeted by Uber), then for cities treated between 2013 and 2015, and lastly, for all cities treated during the full 2013 - 2019 window. While the results show significant positive estimates for the 2013 - 2015 cohorts, including the medium and small size cities treated in later stages yields non significant estimates.

The findings are robust to several alternative specifications, including the exclusion of treated cities where a competing platform (Bolt) entered during the same period and variations in the control group based on different radius thresholds.

The paper is organized as follows. Section 2 presents the literature to which my paper contributes. Section 3 describes the context, the data used and shows some descriptive statistics. Section 4 presents the identification and the empirical strategy. Section 5 contains the main results, followed by a discussion on the potential mechanisms in section 6. The paper concludes with section 7.

2 Literature Review

While evidence and official statistics show that platform work is predominantly migrant labour, research on the intersection of gig economy and ethnic entrepreneurship remains scant (Van Doorn et al. 2023). Also, while some descriptive studies show an over representation of migrants and minorities within platform work, there has been limited attempt to clearly quantify the phenomenon and the take up. Thus, my paper contributes to several strands of the literature.

First, it relates to the recent literature on the impact of the development of the gig economy on labour markets. Barrios et al. (2022) exploit the staggered arrival of Uber and Lyft in U.S. cities and find that the platforms entry is associated with a 5% increase in the number of new business registrations in the area, and an rise in entrepreneurial interest, measured with a 7% increase in the share of internet searches for entrepreneurship-related terms. The paper argues that the gig economy acts as a fallback opportunity for potential entrepreneurs by reducing risk and promoting new business formation. Berger et al. (2017) finds that Uber development in the U.S. expanded total employment in cities where the platform was adopted, reduced earnings among wage employed drivers, but increased hourly incomes for self-employed drivers. Cheng et al. (2024) exploit the staggered implementation of TaskRabbit, a location-based platform for domestic tasks, and find that the platform led to a 7% decline in the number of housekeeping workers, mainly driven by a reduction in the middle-skill workers (such as managres). Low-skill workers (such as janitors) where not impacted. Interestingly, the displaced middle-skill workers were not pushed to unemployment or to other sectors, but were rather driven toward self-employment in the housekeeping sector. The authors thus suggest the need to reconsider labour platforms as a way to reshape existing occupations and stimulate entrepreneurship.

Second, it relates to the literature on ethnic entrepreneurship, which is mainly developed in the United States, but less in France. A large literature documents the high levels of entrepreneurial activity among immigrants, who create firms at higher rates than natives. Recent evidence shows that first-generation immigrants create around 25% of new firms in the U.S., with this share exceeding 40% in some states (Kerr and Kerr, 2020). Existing research has analysed numerous factors to explain group differences in self-employment. One determinant could be human capital, measured by education, work experience and language proficiency. While part of the literature finds positive association between higher levels of education and higher levels of business creation (Fairlie, 2006), another part explains that blocked opportunities in salaried jobs due to human capital barriers pushes certain groups to self-employment (Koussoudji 1988). Another possible channel is personal wealth. Previous studies find that low levels of personnal wealth can explain the low self-employment rates among ethnic groups like Latinos in the United States (Lofstrom and Wang, 2009). Also, for immigrants, legal status matters. Studies find that stronger employer sanction for hiring undocumented immigrants increases self-employment rates (Bohn and Lofstrom, 2012). Lastly, cultural and home country influence are also a possible channel. Akee et al. (2013) find that experience with self-employment in home country increases self-employment in the host country for immigrants.

3 Context and Data

3.1 UberX Platform Entry

Created in the United States in 2009, Uber Society officially launched in France in 2011, initially operating in Paris and Lyon, before expanding to 22 other cities before 2020 (Table 10 in the Appendix). In the early stages of its implementation, it seems that Uber prioritized cities with dense populations, and thus with large polls of drivers and potential customers (Table 1). For example, it implemented first in Paris, where 406 new self-employed drivers registered in 2012, representing 1.02% of all new self-employed workers, and implemented a year later in Nice, where the share of drivers among new self-employed reached 2.56%. From 2017 onward, the platform expanded to smaller cities such as Montpellier, Grenoble, Avignon or Reims.

Table 1: Number and Share of Self-Employed Riders (2012)

Commune	**Count**	**Share (%)**	**Commune**	**Count**	**Share (%)**
Paris	406	1.02	Montpellier	33	0.81
Nice	142	2.56	Bordeaux	23	0.52
Marseille	76	0.87	Lille	22	0.73
Nantes	37	0.98	Cannes	17	1.32
Toulouse	37	0.60	Rennes	17	0.72
Lyon	36	0.46	Toulon	14	0.74
Strasbourg	36	1.24	Aix en Provence	9	0.44
Caen	6	0.48	Grenoble	8	0.36
Orléans	8	0.71	Avignon	7	0.58
Nancy	5	0.43	Saint Étienne	5	0.33
Tours	5	0.36	Reims	4	0.23
Metz	3	0.28			

Note: Results obtained from the SIRENE dataset. Interpretation: In 2012, 406 new drivers registered in Paris, representing 1.02% of all new self-employed workers that year.

While the company officially implemented in France in 2011, the first services it proposed at this time were UberBlack rides, which consist of luxury vehicles driven by professional chauffeurs, primarily targeting business workers. These services did not yet pose significant competition to the traditional taxi industry. Uber's impact on the ride services market emerged in 2013 with the introduction of UberX platform. The service allowed users to directly request a ride on the designated app, and proposed lower prices than taxis, as well as dynamic pricing (while the taxi tariffs are fixed and regulated).

The implementation of Uber led to the significant expansion of the private ride-hailing or VTC (”Voiture de Transport avec Chauffeur”) status. Before the creation of UberX, the VTC profession was more of a niche market, that was regulated under the ”Grande Remise” regime, where drivers operated with luxury vehicles, and where the rides had to be pre-booked, mostly for upscale clients or special events. The development of UberX changed the VTC profession : the entry barriers were lowered, the reservation system became instantaneous through an app and the pricing became more competitive. Today, the company is well implemented in France, which is now considered as the second biggest market for the company in Europe.

Uber platform brings a new and more flexible labour supply model (Table 9 in appendix) in the ride service occupation, attracting a different pool of drivers, particularly individuals from minority groups (Financial Times (2016)). First, in terms of documentation, registering as an Uber driver requires less bureaucracy and less financial investment than registering as a traditional taxi. While both occupations require to have a valid driving license, a residence permit (”carte de résident”) and to complete the mandatory formation, the process to obtain the VTC (”Voiture de Transport avec Chauffeur”) status is much easier and cheaper. In fact, the VTC card is easy to obtain as there are no limits in the number of cards emitted. On the other hand, obtaining a taxi license (Autorisation De Stationnement) is a much tougher process. Taxi drivers have two options to obtain it. In theory, they can get it for free from the local municipalities. But in practice, this option is often not viable as drivers sometimes have to wait several years before receiving their license, as the waiting lists are very long. In fact, the number of new licenses delivered is limited by a quota (numerus clausus). For example, in Marseille, no new license has been created and attributed since the 1960's (La Provence (2025)). Therefore, drivers usually turn to a second option, which is to buy their license on the secondary market. Most often, licenses are sold between retiring taxi drivers and newcomers in the profession, at very high prices. On average, a license is sold at 400 000€ in Nice, 240 000€ in Paris and 100 000€ in Marseille.

Once the license obtained, drivers working for Uber have more flexibility than traditional taxi drivers, especially in terms of earnings. In fact, while taxi drivers have different tariffs for the day and night shifts, or for the weekend shifts, Uber tariffs are much more flexible. The tariffs on the platform vary based on demand peaks, for example when it is raining, when there is a train strike or any other event that increases demand. Also, while VTC drivers can take clients from any department, taxi drivers can only drive within the department where they got their exam. To be able to take clients in other departments, the taxi has to pay for additional professional cards, and is limited to four departments. However, this new flexible model introduced by Uber comes with lower protection and less stability, which may explain why some drivers still prefer to work as traditional taxis, despite the very high financial cost associated with it.

3.2 Riders and Demographics

As drivers have to officially register as self-employed to work with Uber, they can be measured in the SIRENE (Système Informatique pour le Répertoire des Entreprises et de leurs Établissements) dataset, using the APE code ”Passenger transport by taxi” (49.32Z). This source of data contains information on all the new businesses registered in France since 1973. For this particular analysis, the observation period ranges from 2009 to 2019, containing in total more than 12 million businesses. When a person creates an individual business, they are given a unique SIREN code, and are officially registered. The database contains detailed information on each business such as the date of creation, the precise geo-location (with latitude and longitude), the sector of activity (APE codes), the legal form, the gender and the name and family name of the workers. From this information, it is possible to target self-employed VTC and taxi drivers (APE code of 49.32Z and self-employed legal form). Once new drivers are identified, the dataset provides both their first and last name, allowing to proxy for their ethnicity using the NamSor algorithm. An advantage of this dataset is that it includes both the birth name and the married name. It allows for more accurate ethnicity identification for female drivers (although they are a minority) that may use their husband's name. A limitation, however, is that around 11% of self-employed VTC and taxi drivers did not provide a name, making it impossible to proxy their ethnicity. For the remaining individuals, the NamSor algorithm returns the most likely ethnicity for each driver, along with a calibrated probability. The model's accuracy was further improved by incorporating the country code feature which indicates that the workers are based in France. This makes the algorithm rely on the specific distribution of ethnicities and diasporas in France. Once each worker is associated with a proxied ethnicity, the share of "ethnic" workers among the newly registered self-employed drivers can be computed. The resulting dataset contains, for each city at each year, the total number of newly registered drivers (Figure 1), and the share of the different ethnic groups among these new drivers (Figure 2).

Table 2: Example of The Dataset After Ethnicity Approximation

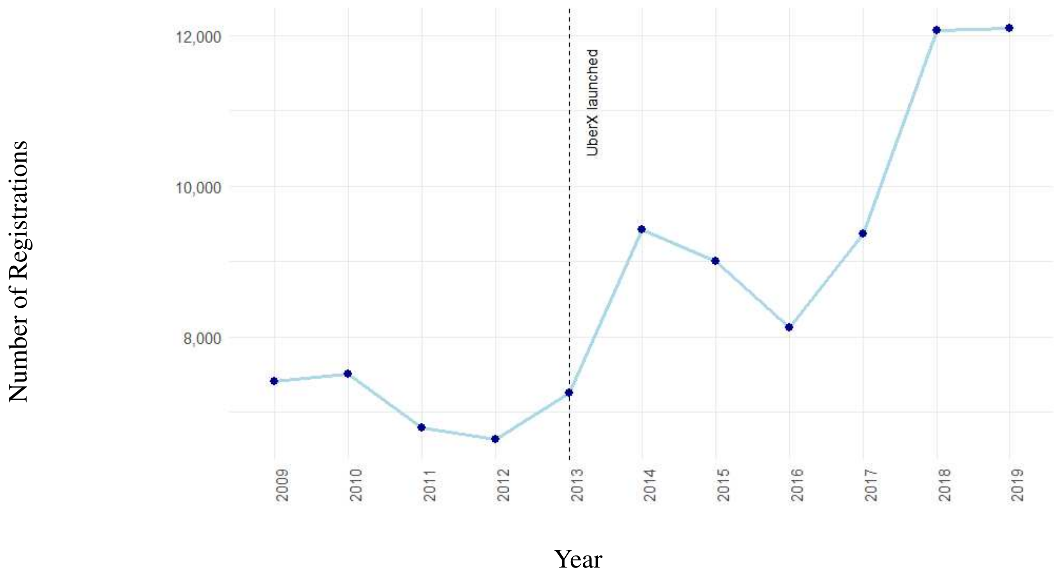
Name	**SIREN**	**Creation Year**	**City**	**APE Code**	**Ethnicity**
Jean Dupont	812345678	2010	MARSEILLE	49.32Z	French
Mohamed Benali	798765432	2017	GRENOBLE	49.32Z	Algerian
Kouassi Yao	765432189	2013	LYON	49.32Z	Ivorian

Note: the names and information in the table is random and does not represent real workers.

Figure 1 illustrates the significant increase in new riders registrations after the launch of UberX in 2013. From 2012 to 2019, the number of new driver registrations went from 7 000 to 12 000. It is important to remind that these numbers do not represent the total amount of active riders, but rather the number of new drivers that register in a given year. For example, drivers that register in 2017 will not be counted in the subsequent years, unless they start another driving activity. Over the period, 82% of new drivers are men.

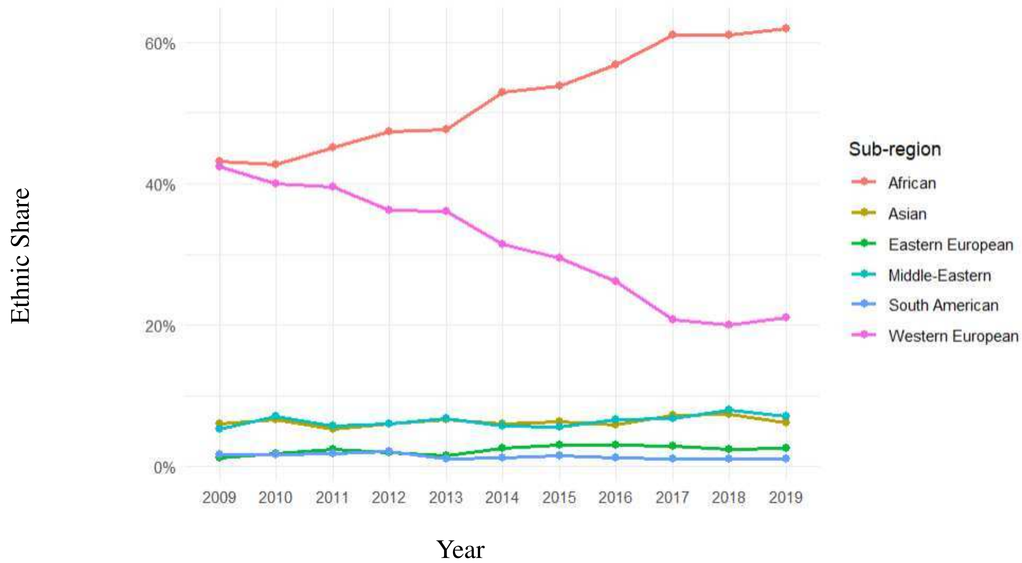
This new form of work not only increased the number of new drivers, but it also seems to have been relatively more attractive for minority groups, notably drivers with African sounding names, compared to others. Figure 2 shows that before the implementation of UberX, the ethnic distribution of new drivers was already changing steadily, with an increase in African minorities and a decrease of Western European drivers. Then, from 2013, the gap widens more rapidly. The share of drivers with African origins increases significantly, making them the majority group with a share of 60% in 2019, while the proportion of new Western European drivers dropped to 20%. The share of the other ethnicity groups seem to stay relatively stable over the period.

Figure 1: Evolution of Yearly VTC and Taxi registrations



Note: figure obtained from SIRENE data. *Interpretation :* each point represent the number of newly registered self-employed with code APE 49.32Z (drivers). It is important to remind that drivers registered in 2014 are not counted in 2015 or further years.

Figure 2: Evolution of VTC and Taxi Ethnic Composition



Note: This figure was obtained from SIRENE data. Interpretation : in 2016, 45% of the new VTC and taxi registrations were from Maghreb minority workers, and 25% were from Western European workers.

4 Identification and Empirical Strategy

This paper aims at estimating the causal impact of platform work on the self-employment activity of ethnic minorities, using Uber as a case study to examine its effect on the ride-hailing sector. More specifically, the goal is to conclude whether the take up was higher among ethnic minorities than for the rest of the population. The identification relies on several points.
First, UberX is taken as a case study as it was the first prominent platform to implement in France and to have a considerable impact on the on the ride service occupation, considering the vivid reaction of the local taxi drivers. Then since UberX is a location based platform (services are provided in a specific geographical area), it allows to measure the outcome of interest at the city level. Lastly, the rollout implementation of UberX in French cities defines a clear treatment. For example, when the platform starts its activity in Bordeaux in 2014, the city is considered as treated during this year, and for the years onward. On the contrary, a city that is far enough from treated cities (to avoid spillovers) and where Uber is not implemented in the 2009 - 2019 period can be used as a control.

Second, before joining the platform, Uber drivers have to officially register as self-employed such that they can be directly measured in the SIRENE dataset. Since the data includes name and surname of the workers, it is possible to proxy for their ethnicity, and have the ethnic composition of new drivers for each city at each year. More specifically, the outcome variable consists in the share of a given ethnic group among all new drivers at the city level in a given year. The group of ethnic workers can vary, depending on the most appropriate definition :

- All workers with a non-French name (the most general one).
- All workers with a non western name.
- All workers with an African name, or an Eastern European name (region specific, including more homogeneous group of workers).

Then an event study is implemented to measure the causal impact of UberX implementation on the share of ethnic minorities among the VTC and taxi drivers registrations.

$$EthnicShare_{it} = \beta_0 + \sum_{k=-5}^{-1} \gamma_k^{\text{lead}} \cdot D_{it}^k + \sum_{k=0}^{6} \gamma_k^{\text{lag}} \cdot D_{it}^k + \alpha_i + \lambda_t + \varepsilon_{it}$$

Where $EthnicShare_{it}$ is the share of ethnic drivers among the new registrations in city i at year t, D_{it}^k is a set event-time dummies that take value one if city i is k years away from initial treatment at time t. For example, if city i (Paris) gets treated in 2013, $D_{it}^{-}3$ is equal to 1 for the year 2010, and zero otherwise. The coefficients γ_k^{lead} and γ_k^{lag} respectively capture the pre-treatment trends and the post-treatment effects. α_i and λ_t capture city and year fixed effects and ε_{it} is the error term. The standard errors are clustered at the city level. The period k = -1 is omitted.

While the Two-Way Fixed Effect (TWFE) is the basic model for staggered adoption, recent literature has shown that its estimates can be inconsistent in settings with variation in treatment timing across units and where the treatment effects are heterogeneous across treatment groups (Sun & Abraham, 2020). I address this possible bias by using the Callaway & Sant'Anna (2021) estimator.

The period of observation starts in 2009 and ends in 2019. This specific window was chosen to avoid any bias from two events : the introduction of the micro-entrepreneur status in France in 2009 (Loi de Modernisation de l'Economie), which significantly increased new registrations from 2008 to 2009, and the COVID-19 lockdown beginning in 2020, which significantly disrupted the ride-hailing activities.

The treatment group consists of all the cities where UberX was implemented within the period of interest. Once UberX is implemented in a city, the city is considered treated for all the subsequent years (the treatment doesn't turn-off). The group consists of Paris and Lyon (2013), Bordeaux Lille Cannes Nice and Toulouse (2014), Marseille Nantes and Strasbourg (2015), Montpellier (2017), Rennes Avignon Aix-en-Provence and Toulon (2018), Grenoble Caen Reims Tours Saint-Etienne Orleans Metz and Nancy (2019).

The control group includes cities that satisfy two criteria. First, they are "never-treated", meaning that UberX never started its activity there, or only later than 2019. Also, they need to be far enough from the treated cities in order to avoid any indirect exposure to the platform effects through spillover. Including such cities could lead to an underestimation of the treatment effect. For example, cities like Versailles, Créteil (near Paris) and Vénissieux (near Lyon) are not suitable controls due to their proximity to some treated cities. To solve for this, I select all cities that are never-treated, and that are outside a 30km radius around the treated cities. The choice of the 30km radius is motivated by a trade-off between avoiding spillover effects and ensuring comparability between control group and treatment group. While a smaller radius increases the risk of spillovers, a larger radius reduces the size of the control group and may select cities that are too distant from the treated cities. Moreover, the 30km radius makes sense knowing that the average Uber ride distance is of 10km, making the radius large enough without being too restrictive.

5 Results

5.1 Impact On The Number of Riders

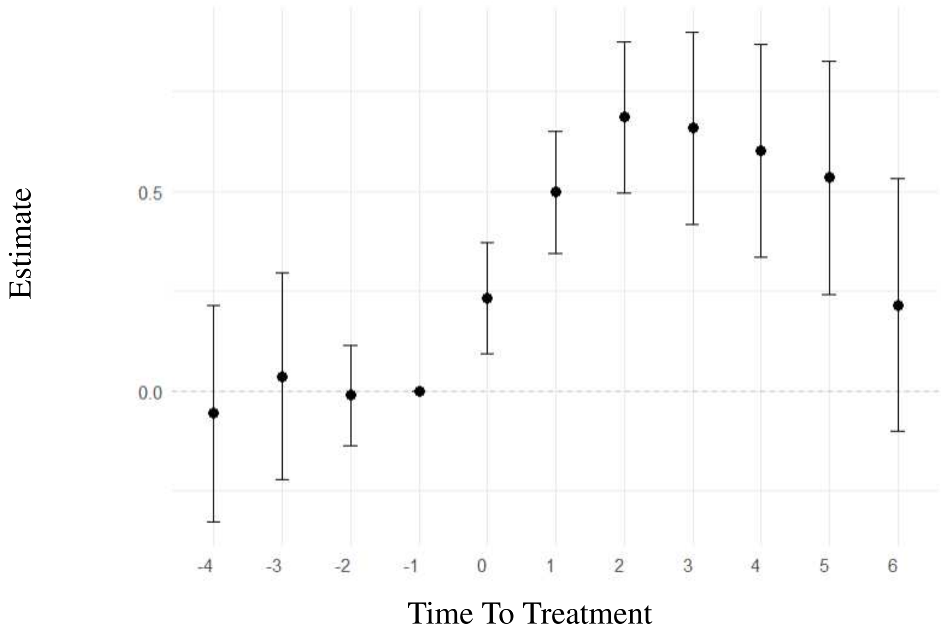
A first event study is estimated to measure how much the platform impacted the yearly number of new drivers registrations. The estimation model is the same as the one presented above, except that the outcome variable here is the log of new drivers at year t in city i.

The results indicate that the platform significantly increased the number of new drivers registrations each year, with an increasing magnitude of the impact over time. On the first year when Uber starts its activity, the number of new registrations increases by 26%, and the third year after treatment, the number increases by 93%. The pre-trends in the graph support the parallel trends assumption.

5.2 Impact On The Ethnic Composition Of New Drivers

The outcome of interest in this study is the share of ethnic minority groups among newly registered drivers each year, at the city level. It is important to remind that the SIRENE data doesn't allow to distinguish between immigrants and second or third generation immigrants, although they face some common barriers on the labour market. The definition of the "ethnic minority

Figure 3: Event Study Estimates On The Number Of New Drivers

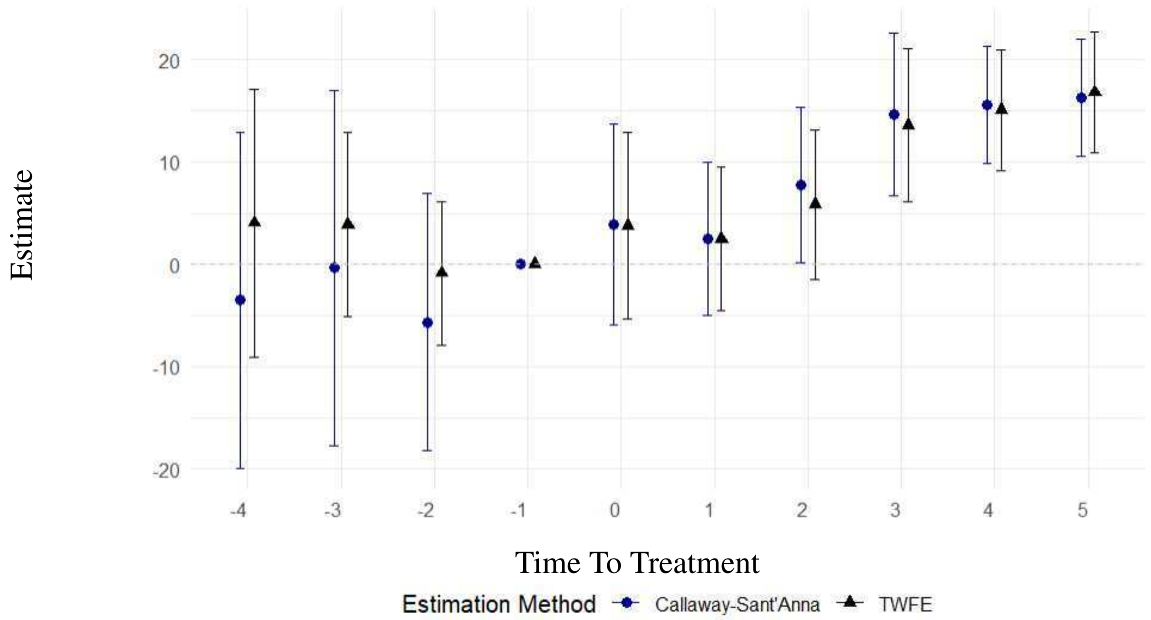


Note: since the regression is in log-level, the coefficients are interpreted as follows - the first year after treatment, the number of new registrations increased by (exp(0.5) - 1) x 100 = 64.87%.

group" depends on which ethnicities are included. For example, a broad definition includes any name combination that is not classified as French. However, the results from this classification are not statistically significant, likely because it groups together very heterogeneous ethnic groups. Individuals of European origin do not face the same labour market challenges or share the same characteristics as those from African or South Asian backgrounds. In the main specifications, more homogenous groups are considered, such as African ethnicities, Eastern Europeans or South Asians.

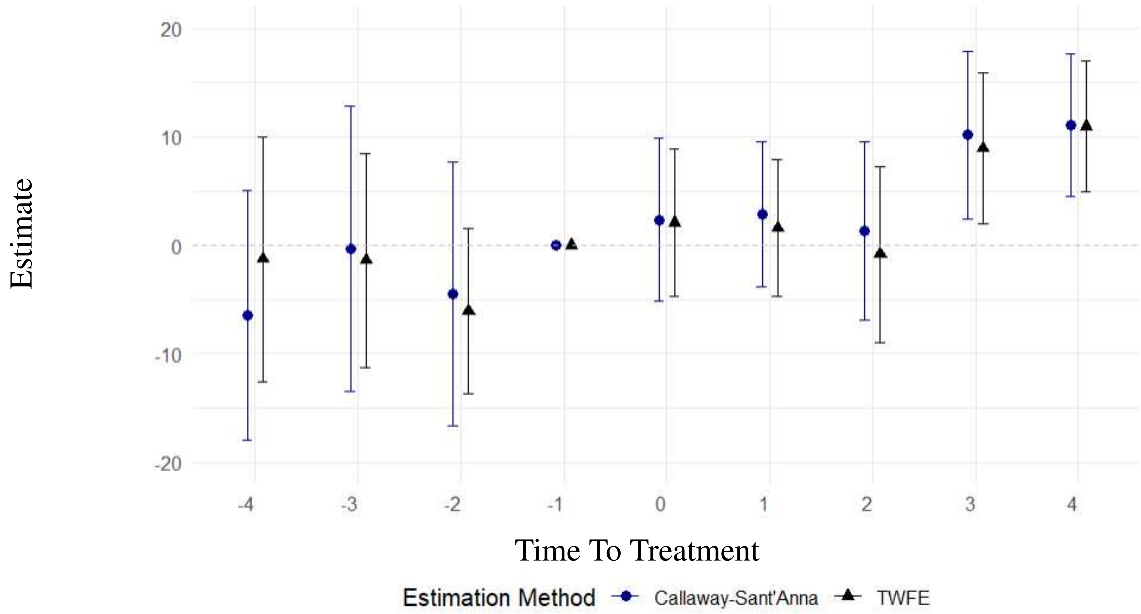
There are three different sets of results. The first one includes the largest treated cities, where Uber implemented in the early stages : Paris and Lyon (2013) and Bordeaux, Lille, Cannes, Nice and Toulouse (2014). For the first group of cities (2013 - 2014), the average treatment on the treated (ATT) indicates that over the period, the share of new drivers with African background increased by 11.54 percentage points (Table 14 in appendix). The estimate is statistically significant. Then, the dynamic event study indicates that the impact of Uber takes a few years to take place, as the positive and significant impact is observed around years 3, 4 and 5 after treatment, with an estimate of around 15 percentage points (Figure 4).

Figure 4: Event Study Estimates For The African Ethnic Group (2013 - 2014 cohorts)



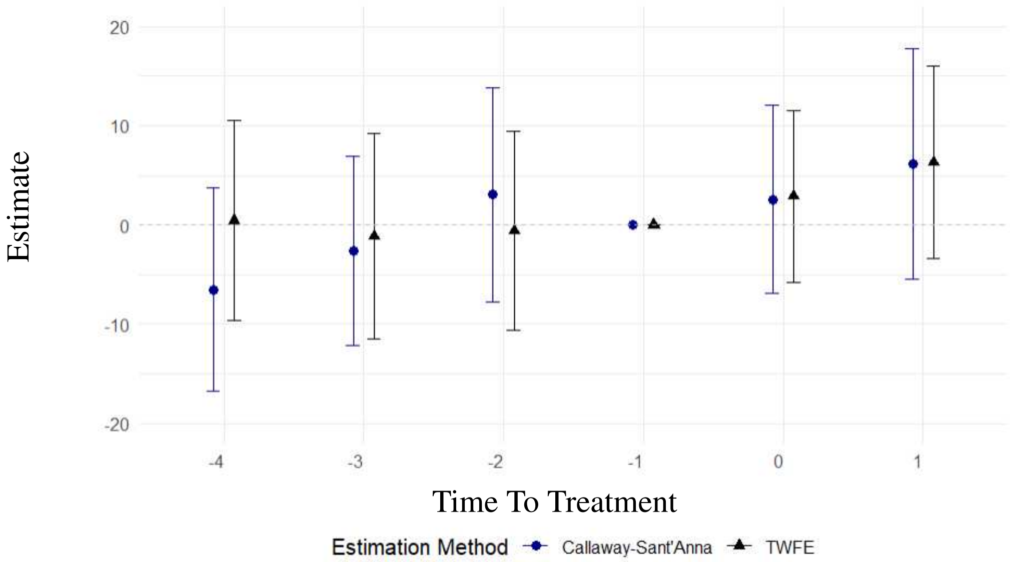
The second set of results includes the cities that are treated between 2013 and 2015, adding Marseille, Strasbourg and Nantes (2015). In order to avoid composition effect and keep the number of cities in the treatment group stable, the time window is reduced to 4 years after the treatment. When adding these cities to the treatment group, the impact of Uber is lower, but stays significant and positive, with an average treatment effect of 5.57 percentage points. Again, the effect is significant around 3 years after the treatment, with an estimate of around 12 percentage points (Figure 5).

Figure 5: Event Study Estimates For The African Ethnic Group (2013 - 2015 cohorts)



Finally, the last set of results is obtained from the complete treatment group, including all the cities treated between 2013 and 2018. The average treatment effect is of 4.37 percentage points, but is non significant. The event study shows no significant impact, which is in line with the previous graphs showing that the impact of Uber was not observed in the very first years following treatment.

Figure 6: Event Study Estimates For The African Ethnic Group (2013 - 2019 cohorts)



Overall, the results presented above provide causal evidence that platform work, in the specific case of UberX, changed the ethnic composition of the ride-hailing occupation, with a significantly higher take up of African ethnic minorities. The impact on other ethnic groups was tested, specifically on Eastern Europeans and South Asians, and no significant estimate was obtained. Interestingly, when the analysis is restricted to individuals from former French colonies, the ATT is significant, with an estimated effect of 8.29 percentage points (Table 14 in the appendix). This result suggests that ride-hailing jobs through Uber also attracted immigrants and minorities likely to speak French, which helps to rule out language barriers as a major driver of platform attractiveness. Another point that supports this idea is that language proficiency is a mandatory prerequisite for engaging in self-employed driving job.

The heterogeneity analysis shows that the ATT for the 2013 - 2015 cohort seems to be mainly driven by early adopters, which are cities treated in 2013 and 2014. In fact, Paris and Lyon (treated in 2013) show a significant ATT of 13.39 percentage points, while Bordeaux, Lille, Cannes, Nice and Toulouse (treated in 2014) show a significant ATT of 7.75 percentage points (Table 13 in the appendix). The estimates for later-treated cities (2015 - 2019) are not statistically significant. One possible explanation is that the effect on drivers' ethnic composition takes time to realize, typically three to four years after the treatment. Since the observation window is limited to 2019, it is likely not far enough in time to capture the full treatment effect for the later cohorts. This may attenuate the estimated effect for these groups.

5.3 Robustness

A first test consist in changing the exclusion radius that is used to select appropriate control cities. Radius from 15 to 50 kilometres are tested, and the ATT estimate on the African ethnic group remains stable and significant, within a 9.61 to 10.62 percentage point range (Table 14 in appendix).

Then, one potential threat that could have biased the results is the introduction of UberPOP over the 2014 - 2015 period. This specific version of the platform, launched in 2014, allowed any private individual with a vehicle to become a driver. This new service was met with strong opposition from traditional taxi drivers, who viewed it as illegal and unfair competition, due to the important lack of regulations. As a result, UberPOP was banned in July 2015. One way this could bias the results is that UberPOP gained significant popularity and was even more accessible to new drivers than UberX, potentially causing a spike in the number of new drivers during those two years. However, because UberPOP drivers were private individuals, they were not required to officially register as self-employed to earn their income. As a result, many of them are unlikely to appear in the SIRENE database, which only contains officially registered self-employed workers.

Another possible threat is the introduction of Bolt VTC, a very similar ride-hailing platform, in Paris in October 2017 and in Lyon in December 2018. If Bolt VTC arrived before Uber, the results observed above would fail to capture and isolate the impact of UberX. This can be checked by removing the two cities from the treated group and see if the results change significantly. The estimated coefficients obtained for the cities treated between 2013 and 2015 are still significant and show smaller magnitude, with an ATT of 2.9 percentage points (compared to 5.57 percentage points when Paris and Lyon are included).

6 Mechanisms and Discussion

Overall, the findings suggest that Uber platform increased access to self-employment in the ride-hailing sector relatively more for African minorities than for other groups. However, the mechanisms behind this higher uptake among workers with an African background cannot be explained using the SIRENE data. But these results still raise interesting open questions that are worth discussing. The discussion is base on descriptive evidence on immigrant workers and platform workers obtained from the French Labour Force Survey (LFS) and the Population Census. The French LFS contains individual and detailed information on a representative sample of the population in France. This source of data is used to obtain descriptive information on platform workers, since a specific question on this new form of work was introduced in the surveys of 2021 - 2023. The French Population Census, provided by INSEE, contains information such as the unemployment rate among immigrant population at the city and the country level or the size of the active population and the share of independents and salaried workers.

6.1 Ethnic Entrepreneurship and Platform Work

A large body of literature documents a higher prevalence of entrepreneurship among the foreign-born population compared to natives in several developed countries. For instance, Fairlie and Lofstrom (2015) find that immigrants account for more than 24.9% of all new business owners in the United States. While most of the literature on this subject has its roots in the United States, evidence obtained from the French Population Census (INSEE) indicates that ethnic minorities in France also exhibit a higher tendency toward self-employment (Table 3). In the 2006 - 2013 period, immigrants represent 11.36% of the active population, and over 13.93% of the independent workers, suggesting an over-representation of 2.57 percentage points.

Table 3: The Over-representation of Migrants In Self Employed Group

Year	Group Type	Share Active (%)	Share Independents (%)
2006-2013	Immigrants	11.36	13.93
2006-2013	Natives	88.64	86.07
2014-2021	Immigrants	12.80	14.94
2014-2021	Natives	87.20	85.06

Note: Obtained from French Population Census.

This over representation is even more striking concerning platform work, which is predominantly migrant labour. Over the 2021 - 2023 period, while only 11% of the employees and traditional independent workers are immigrants, over 23% of platform workers are migrants, a ratio twice as high.

Table 4: Demographics of Different Labour Market Groups

	Active	**Employee**	**Independents**	**Platform**
Migrant Share (%)	11.74	11.16	11.28	23.00
Women Share (%)	48.90	50.62	37.10	43.34
Average Age (Years)	41.70	41.45	46.45	42.04
College Diploma (%)	44.60	45.20	50.90	54.50

Note: Table obtained from the French LFS (INSEE). Around 23% of platform workers are immigrants, and 43.34% are women.

Although these immigrant platform workers are also present in high skill occupations requiring high level of education (Managers, Professionals) (Table 5), their over-representation within the low-skill taxi occupation draws attention : while 38.20% of immigrant platform workers are working in the plant and machine operators occupation (the large majority being taxi and VTC drivers, only 3.98% of French platform workers are in this occupation. With the service and sales and technicians occupations, it is the only occupation that shows such a large gap in participation. These ratios are in line with the relatively higher take up of African minorities in the ride-hailing activity compared to other groups, after UberX implementation.

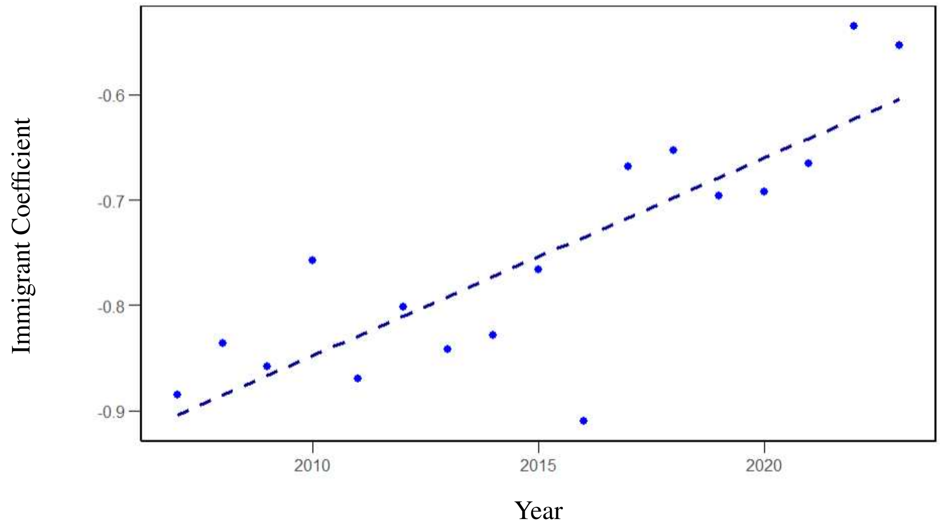
Table 5: Platform Workers by ISCO Occupation and Immigration Status

ISCO Occupation	Immigrant (%)	Native (%)
1. Managers	12.49	10.96
2. Professionals	27.05	36.31
3. Technicians	5.90	16.73
4. Clerical Support	1.48	0.13
5. Service & Sales	7.30	18.96
6. Skilled Agricultural	1.26	2.64
7. Craft & Trades	3.61	8.08
8. Plant & Machine Operators	38.20	3.98
9. Elementary Occupations	2.71	2.20

6.2 Disadvantage theory

There are variety of reasons why migrants are more likely to opt for self-employment. Early theories suggest that ethnic entrepreneurship can be understood as a reaction to blocked opportunities in the labour market. This disadvantage-based explanation still holds true today as unemployment rates are much higher among minority groups than among the native population (Figure 7)

Figure 7: Immigrant Coefficient over Time



The figure plots the results for a logit regression performed on the French LFS individual data for each year in the period 2007 - 2023 :

$$\text{Employed}_i = \beta_0 + \beta_1 \text{Immigrant}_i + \gamma X_i + \varepsilon_i$$

Where $Employed_i$ is a binary variable indicating whether person i has a job or not, $Immigrant_i$ a binary variable indicating whether the person is immigrant or native, and X_i is a vector of individual controls that can affect employability (gender, age, age squared, diploma and number of children under 3 years old). Each dot plotted in the graph corresponds to the estimated coefficient for each year for the binary variable $Immigrant_i$. It quantifies how much lower is the probability of an immigrant to obtain a job relative to a native with similar individual characteristics. The graph indicates that for each year, the coefficient of interest is negative, meaning that immigrants have a lower probability of getting a job relatively to natives, which confirms that they face some sort of entry barriers to employment. Overtime, the coefficients become less and less negative, showing a reduction in the employment gap. In 2007, the probability to obtain a job was 59.4% lower for immigrants relative to natives with similar characteristics, while in 2023, the gap lowered to 45% (since the regression is in log-level, the percentage is obtained by doing (exp(-0.6) - 1) x 100 = 45%.

This gap in employment opportunities may be due to different channels. A first explanation is that external factors such as a deficit of education, experience or language skills creates barriers to salaried employment, and pushes foreigners into self-employment. Regarding education, if this was completely the case, then we would observe that the major part of immigrants working in the ride-hailing occupation actually have little to no education. However, the descriptives from the French Labour Force Survey show that a non negligible part of immigrant ride-hailing workers have a college education (Table 6). Precisely, over 20% of immigrant drivers hold a college degree, compared to only 7% of their native French colleagues. The share of workers with no diploma however is very similar in both groups. Thus disparity in the share of educated workers suggests a greater degree of skill mismatch among immigrant workers, which may reflect challenges such as the non-recognition of foreign qualifications, rather than a lack of formal education.

Table 6: Educational Attainment Among Taxi Drivers By Immigration Status

Group	**College Education**	**High School Diploma**	**No Diploma**
Immigrants	0.1986	0.3404	0.4610
Natives	0.0775	0.4430	0.4795

As for previous experience, a significant share of immigrants working in the gig economy were previously unemployed (Table 7). Specifically, 27.8% of immigrant platform workers had been unemployed, compared to 21% of their native counterparts. This suggests that the gig economy may serve as a stepping stone out of unemployment for some immigrants. However, many immigrants in the gig economy already had a job beforehand. In fact, 32% of them were previously in salaried jobs, and 5.6% had been self-employed. This highlights the diverse profiles of those entering the gig economy. Some view it as their first most accessible option for stepping out of unemployment, while others transition from traditional salaried employment to platform-based self-employment.

Table 7: Employment Situation By Category

Category	Previously Unemp.	Previously Employee	Previously Indep.	Previously Stud.
Employees	0.134	0.284	0.015	0.114
Immigrant Platform Workers	0.277	0.318	0.056	0.066
Independent Workers	0.122	0.280	0.087	0.045
Native Platform Workers	0.214	0.296	0.103	0.090

Lastly, in the case of ride-hailing occupations, language barriers are unlikely to explain the over representation of immigrants in the gig economy. In fact, basic proficiency in French and English is a mandatory requirement to pass the VTC and taxi certification exams. So, there is already a selection filter in place : only immigrants who meet these language requirements can work as drivers - whether it is as traditional taxi or as VTC drivers for Uber.

Other than a lack of human capital, a lack of mobility due to poverty or discrimination may also drive minorities toward self-employment. In France, immigrants are over-represented in priority neighbourhoods ("Quartier Prioritaire de la Politique de la Ville"). These neighbourhoods refer to specific urban areas in France that are identified based on social, economic and geographical criteria, typically having high levels of poverty, unemployment, social exclusion and poor educational outcomes. 23% of immigrants live in these areas, compared to only 7% of the total 15 - 59 years old population. Almost 30% of Maghreb and Sub-Saharan Africa live in these neighbourhoods. The same situation is observed for those with two immigrant parents, where 20% of them live there (INSEE, 2023). Living in these areas can limit the opportunities of employment due to geographical discrimination. Bunel et al. (2016) note a remarkable differential in the success rates by place of residence. The success rate for being invited to a job interview for waiters of CAP level doubles for candidates living in favourable locations. The success rate is of 9.6% if they live in areas near Seine-Saint-Denis (priority neighbourhood) and rises to 19.9% for the candidates living near Paris.

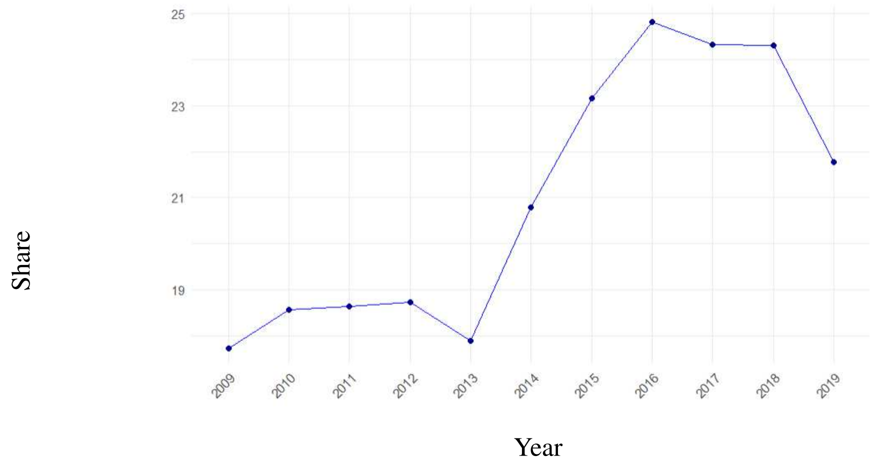
From the SIRENE database, I use the geolocation available for each self-employed worker to obtain their personal address, and to determine whether they are located within a priority neighbourhood or not. From there, I obtain that accross France, over the 2009 - 2019 period, around 20 325 drivers live in such neighbourhoods, representing over 21% of all drivers. In comparison, only 5% of the overall French workforce lives in a priority neighbourhood (Botton, 2022). This phenomenon is even more pronounced in certain cities, such as Lille, where 40.3% of drivers live in priority areas.

Table 8: Share Of Drivers Living In Priority Neighborhoods (QPV)

City	**Total Number of Drivers**	**% Drivers Living In QPV**
France	95427	21.24
Lyon	575	13.39
Lille	362	40.33
Paris	4582	12.40
Bordeaux	215	19.53
Toulouse	467	21.41
Montpellier	228	18.42
Marseille	843	27.76
Nice	1062	14.69

And interestingly, the share of drivers from priority areas have increased since UberX development in France in 2013. This descriptive evidence suggests that platform work made the ride-hailing activity more accessible and more attractive to workers from disadvantaged areas, where unemployment rates are relatively higher than in the rest of the French territory.

Figure 8: Evolution of the Share of Drivers Living in Priority Areas



6.3 Cultural theory

Factors other than the disadvantages listed above can explain this propensity to self-employment. Cultural-based theories explain that migrants and minority groups are equipped with cultural traits that favour self-employment, such as dedication to hard work and acceptance of risk (Masurel et al. 2004). In another paper, for example, Akee et al. (2013) argue that experience with self-employment in the home country before migrating is an important determinant of the decision to enter self-employment in the host country. They find that home country self-employment increases self-employment in the United States by about 7 percentage points.

7 Conclusion

This paper leverages the rollout implementation of UberX in France to study how gig work platforms affect the creation of new self-employed activities, with a focus on ethnic minority participation in the ride service sector. Using administrative data on business registrations, I proxy drivers' ethnicity through an algorithm based on their first and last names. This approach yields city-year levels of newly registered independent drivers, and their ethnic composition. Results from the event study show that UberX's introduction significantly increased the number of newly registered drivers, and raised the share of drivers with African-sounding names by an average of 11.5 percentage points. These results show a higher take up of the platform among drivers with African background compared to drivers with other ethnic backgrounds. While the results do not allow me to identify the mechanisms behind this differential uptake among ethnic groups, it leaves open several interesting considerations on the impact of platform work on labour market access inequalities.

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9 Appendix

9.1 Platform Work

Online platform work designates a new form of self-employment where digital platforms directly match service providers and customers, for working contracts that can range on a few minutes duration to longer term contracts. These platforms can be divided into two groups. First, web-based platforms are used for jobs that can be performed remotely (translation, web development, graphic design). Second, location-based platforms are used for jobs that are performed in a specific area (ride-hailing, cleaning service, handymen). The jobs performed in this second type of platforms correspond to what is commonly designated as the ”gig economy”. It corresponds to the branch of online-platform work that is used for low-skill occupations. An important and new job-characteristic that these platforms offer is a great flexibility in the earnings and the working schedule as all the services are directly provided on-demand. Also, it is characterised by much lower barriers to entry as it significantly lowers the effort and costs to build a business and a network. The number of platform workers in France is estimated at around 600 000 in 2023 (2%) of the employed population and about 28 millions in the European Union (Mikael Beatriz (Dares) 2024).

9.2 The Differences Between VTC and Taxi Procedures

Table 9: Summary of Main Steps and Differences: VTC Driver vs Taxi Driver

Step	**VTC Driver (Uber)**	**Taxi Driver**
1. Preliminary Requirements	- Driving license (category B) held for at least 3 years - Clean criminal record - Medical check-up	- Driving license (category B) held for at least 3 years - Clean criminal record - Medical check-up - First aid training (PSC1)
2. Training	- Not mandatory - 50 to 300 hours - Cost: €400 to €3,000	- Not mandatory - Similar to VTC training
3. Exam	- Fee: €200 - 2 parts: written (regulations) and practical (driving)	- Similar fee and exam structure
4. Professional Card	- Valid for 5 years - Cost: €60 - Allows operation throughout France	- Valid for 5 years - Cost: €60 - Valid only in the department where exam was passed - Can request cards for up to 4 departments
5. Registration	- Mandatory - Cost: €170 - Online registration - Renewal every 5 years	- Procedures vary by department
6. License (Autorisation de Stationnement - ADS)	- Not applicable	- Obtained from municipality - Either free but with long waiting lists or bought on secondary market - Price range: €30,000 to over €300,000 depending on city - Quota limits number of licenses issued
Regulation and Tariffs	No quota on the number of VTC drivers Quota on taxi licenses (numerus clausus) Flexible tariffs set by platform for VTC drivers Fixed and regulated tariffs for taxi drivers	

9.3 UberX Rollout Implementation In France

Table 10: Uber product launch dates by French city

City	Product / Launch Date
Paris	Berline – Dec 2011 Van – Nov 2012 UberX – June 2013 uberPOOL – Nov 2014 Uber for Business – Oct 2014 Uber Eats – Oct 2015 Uber Green – June 2016 Uber Acces – Oct 2017 uberPOP – Feb 2014 Jump E-bikes and e-scooters – April 2019
Lyon	uberX – March 2013 Berline Uber Green – Sept 2019 Comfort – June 2020
Lille	uberX – June 2014 Green – Sept 2018
Bordeaux	uberX – Sept 2014 Green – Sept 2018 Comfort – June 2020
Nice / Cannes	uberX – Sept 2014 Berline Van Green – Sept 2018

City	Product / Launch Date
Toulouse	uberX – Sept 2014 Uber Green – Feb 2020 Comfort – June 2020
Marseille	uberX – June 2015 Berline Uber Green – Feb 2020 Comfort – June 2020
Nantes	uberX – June 2015 Green – Feb 2020
Strasbourg	uberX – June 2015 Uber Green – Sept 2019
Montpellier	uberX – Sept 2017 Uber Green – June 2020
Rennes	uberX – Apr 2018 Summer pop-up uberX – July/August 2018 (limited launch)
Avignon, Aix, Toulon	uberX – Sept 2018 Berline in Toulon and Aix
Grenoble	uberX – Jan 2019
Caen, Reims, Saint Etienne, Tours	uberX – March 2019 Uber Green – June 2020 in Reims
Rouen	uberX – June 2019 Uber Green – June 2020
Orléans, Metz, Nancy	uberX – Sept 2019

9.4 Ethnic Minority Groups

African ethnic group : Algerian, Moroccan, Tunisian, Egyptian, Rwandese, Congolese (Kinshasa), Togolese, Niger, Zambian, Chad, Mauritanian, Guinean, Comoros, Cameroonian, Senegalese, Mali, Nigerian, Liberia, Beninese, Ivorian, Congolese, Tanzanian, Ethiopian, Ghanian, Malgasy, Somalia, Lesotho, Sudanese, Kenyan, Gambian, Burkina Faso, Mauritius, Gabon, Burkina Faso, Gabon, Burundese, Namibian, Botswana, Ugandan, Malawi, Mozambican.

Eastern Europe ethnic group : Armenian, Romanian, Russian, Lithuanian, Polish, Serbian, Ukrainian, Georgian, Albanian, Hungarian, Bulgarian, Latvian, Moldova, Czech, Montenegrin, Slovanian.

South Asian ethnic group : Indian, Pakistanese, Bangladeshi, Sri Lankan, Nepalese, Bhutanese.

Former French colonies group : Algerian, Congolese (Kinshasa), Tunisian, Moroccan, Guinean, Burundese, Chad, Rwandese, Comoros, Congolese, Senegalese, Mali, Laos, Beninese, Niger, Cameroonian, Malagasy, Ivoirien, Burkina Faso, Gabon, Togolese, Mauritanian, Vietnamese, Cambodian, Lebanese.

9.5 Drivers Demographics

Table 11: Gender Composition of Self-Employed VTC Drivers by Year (%)

Gender	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Male	82.7%	85.1%	85.6%	84.6%	81.1%	81.6%	79.6%
Female	6.1%	4.6%	4.6%	5.0%	3.7%	3.6%	4.3%
Missing	11.2%	10.3%	9.8%	10.4%	15.2%	14.8%	16.1%
Non Missing Obs	7,256	9,424	9,008	8,129	9,366	12,057	12,088

Table 12: Ethnic Composition of New Self-Employed VTC Drivers by Year (%)

Ethnic Group	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
African	43.13	42.69	45.07	47.30	47.61	52.89	53.85	56.82	61.00	61.01	61.91
Asian	6.00	6.67	5.37	6.10	6.60	6.09	6.34	5.98	7.29	7.45	6.26
Eastern European	1.33	1.82	2.47	2.06	1.64	2.62	3.09	3.13	2.88	2.43	2.54
Middle-Eastern	5.38	7.09	5.79	6.10	6.80	5.79	5.70	6.65	6.89	7.99	7.08
South American	1.72	1.75	1.80	2.14	1.19	1.22	1.51	1.20	1.14	1.07	1.17
Western European	42.42	39.97	39.49	36.31	36.16	31.39	29.52	26.23	20.78	20.05	21.04
Non Missing Obs	5,629	5,879	5,216	4,954	5,558	7,050	6,969	6,272	6,731	8,777	8,723

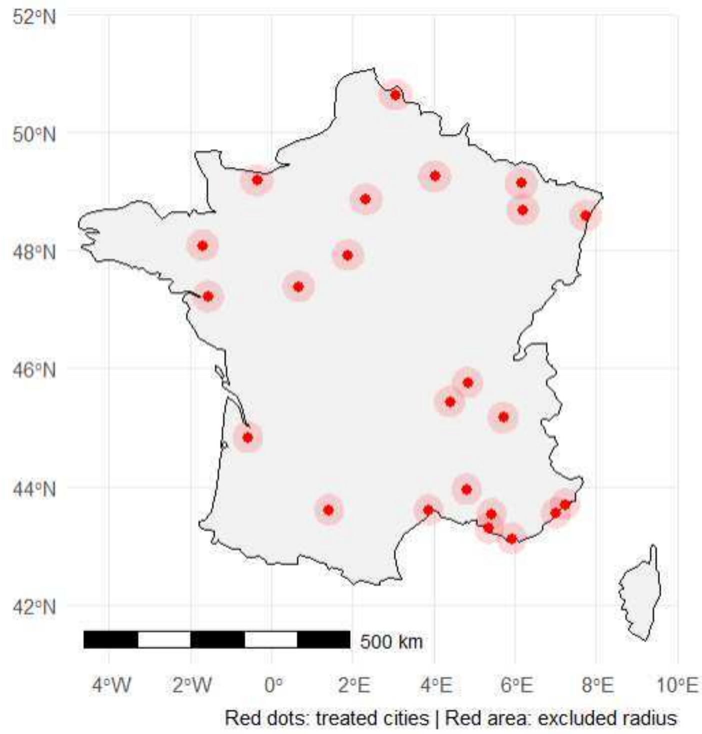
9.6 Identification and Empirical Strategy

Treatment Groups :

- First Set of Results : Paris and Lyon (2013), Bordeaux, Lille, Cannes, Nice and Toulouse (2014).
- Second Set of Results : Paris and Lyon (2013), Bordeaux, Lille, Cannes, Nice and Toulouse (2014), Marseille, Nantes and Strasbourg (2015).
- Third Set of Results : Paris and Lyon (2013), Bordeaux, Lille, Cannes, Nice and Toulouse (2014), Marseille, Nantes and Strasbourg (2015), Montpellier (2017), Rennes, Avignon, Aix-en-Provence and Toulon (2018).

Control Group : the control group is the same for all the different treatment sets, and consists in all the never-treated cities that are outside a 30 kilometre radius from the treated units.

Figure 9: Map of Treated Cities and The Exclusion Radius



Note: Cities outside the red circles are included in the control group.

9.7 Results

Table 13: Heterogeneity ATT Estimates by Treatment Groups

Specification	2013	2014	2015	2017–2019
ATT Estimate	13.39**	7.75*	-2.83	6.90
Std. Error	4.97	2.61	2.25	9.40
95% CI (Lower)	3.65	2.64	-7.25	-11.53
95% CI (Upper)	23.14	12.86	1.58	25.33
Observations	6,320	6,005	6,469	6,484

Table 14: ATT Estimates by Ethnic Group

Specification	African	Eastern European	Middle Eastern	South Asian	Former French Colonies
ATT Estimate	11.54***	9.86	6.83	0.74	8.29***
Std. Error	2.87	6.20	3.85	6.19	1.91
95% CI (Lower)	5.92	-2.29	-0.73	-11.38	4.55
95% CI (Upper)	17.16	22.01	14.38	12.87	12.03
Observations	3,254	3,254	3,254	3,254	3,254

9.8 Robustness

Table 15: ATT Estimates by Exclusion Radius

Specification	10km	15km	20km	25km	30km	35km	40km	45km	50km
ATT Estimate	9.61***	10.34***	10.62***	10.17***	10.11***	9.81***	9.22***	9.52***	9.56***
Std. Error	2.58	2.49	2.68	2.64	2.62	2.57	2.67	2.99	2.72
95% CI (Lower)	4.55	5.47	5.36	5.00	4.99	4.78	3.98	3.65	4.22
95% CI (Upper)	14.66	15.22	15.88	15.34	15.24	14.85	14.45	15.38	14.90
Observations	5,696	4,896	4,263	3,736	3,254	2,931	2,743	2,557	2,389