Deliver Us from Crime?
Online Platforms, Gig Jobs, and Offending*

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Abstract

Online gig platforms create new job opportunities for minorities and marginalized populations. Leveraging the staggered rollout of food delivery platforms in France, we study their impact on employment and crime rates. Our staggered difference-in-differences reveal that platform entry in a local labor market significantly increases employment for low-skilled workers, especially youth and migrants, as reflected in the rise of registered riders. This job growth coincides with modest declines in male migrant unemployment and welfare claimant rates. We also observe notable reductions in recorded crime, particularly violent offenses, low-skilled thefts, property destruction, and drug-related incidents. These results underscore the gig economy's role in encouraging participation of marginalized groups in lawful economic activities.

Keywords: Gig-economy, crime, digital platforms

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1 Introduction

Online gig platforms can provide unique opportunities for minorities and marginalized populations who face discrimination in the job market. We study the impact of gig jobs on employment and crime through the increase in legal jobs opportunities created by the rollout of online food delivery platform in France. Following Becker (1968), we assume that improved legal labor market opportunities could deter individuals on the margins of criminal involvement by increasing the opportunity cost of engaging in illegal activities, such as drug dealing. The staggered rollout of delivery platforms in France, provides a unique opportunity to analyze the causal impact of delivery jobs in criminal activities and employment in one of Europe's largest online food delivery markets.[1]

Since 2015, online food delivery platforms like Uber Eats and Deliveroo have facilitated the rapid growth of delivery jobs in France. Unlike ride-sharing platforms, food delivery platforms in Europe rely on bicycle riders to transport food from restaurants to users. Gig jobs are characterized by low barriers to entry, minimal investment requirements, and flexible work arrangements (Einav *et al.*, 2016; Hall & Krueger, 2018; Chen *et al.*, 2019; Guo *et al.*, 2024), making them highly accessible to young, low-skilled men and migrants. At the same time, empirical evidence suggests that young and low-skilled men face a high unemployment rate and are more likely to commit offenses.[2,3] The overlap in demographics between the convicted population and riders, who are male, young and low-skilled, suggests that the deterrent effect could be economically significant. Evidence also suggests that discrimination is particularly high in France for low-skilled jobs and improving employment opportunities for migrants reduces their likelihood of engaging in criminal behavior.[4] This idea is echoed by migrants in France, who "needed work, and that riding a bike, even on precarious terms, was better than more nefarious ways of making money like selling drugs" (New York Times, June 16th, 2019).[5]

[1] See https://dashmote.com/articles/the-ongoing-food delivery-race-in-europe.

[2] In 2015, the OECD reported a NEET (Not in Education, Employment, or Training) rate of 15.8% among young men aged 20 to 24. The United States recorded a slightly lower NEET percentage at 15.3%, while France's rate was significantly higher at 21.7%. Youth unemployment is notoriously high in France, in particular for low-skilled individuals (Cahuc *et al.* (2013)).

[3] In 2015, data from the French Ministry of Justice indicate that 67% of individuals convicted were between the ages of 18 to 40 years old, with 89.8% being men. Similarly, data from the United States Department of Justice indicate that 57.9% of sentenced prisoners were between 18 and 40 years old, with 92.9% being men.

[4] See Marie & Pinotti (2024) for a review.

[5] https://www.nytimes.com/2019/06/16/business/uber-eats-deliveroo-glovo-migrants.html.

While gig jobs offer new employment opportunities and have the potential to reduce crime, there are legitimate concerns about job insecurity and lack of social protection for gig workers.[6] These poor working conditions could fuel violent local opposition to the introduction of these platforms. There is also the possibility that riders themselves become targets of crime. This would result in a positive relationship between the entry of gig economy platforms and crime rates in a given economic area. These conflicting aspects raise our empirical research question: Can access to gig work, amidst its benefits and vulnerabilities, help reduce crime?

To address this tension, we use an original dataset measuring the staggered rollout of online food delivery platforms in France, from 2012 to 2019.[7] For example, Deliveroo entered Paris and the southwestern city of Bordeaux in 2015, while Uber Eats started operating in Paris in 2015 and expanded to the southeastern city of Lyon in 2016. Since riders are not directly employed by the platforms, we can measure their numbers by leveraging the fact that they are required to register as independent contractors. Descriptive evidence based on rider names shows that riders are predominantly male, with name origins indicating they are largely 1st- and 2nd-generation individuals of African descent. We also measure the intensity of crime and the level of employment in a given geographical area.

A critical aspect of our methodology is to address the potential endogeneity of platform entry in a given location. The concern here is that the platform decision to enter a location may not be independent of existing economic conditions, which are also correlated with crime rates. To address this concern, our identification strategy relies on comparing already "treated" locations—those where online platforms have entered at a point in time—with those that will be treated in the future or never treated.

Our staggered difference-in-differences results show that the entry of delivery platforms into a location increases the number of registered riders and reduces the rate of people outside the labor force. The rollout of the platforms decreases drug-related crime rates.[8]

[6] See Euronews Business' survey: Uber and Deliveroo may cost more soon: Are you ready to pay. Last retrieved, December 2023.

[7] Our analysis is limited to the pre-2020 era to avoid any bias from the COVID-19 pandemic and subsequent home lockdowns that substantially reduced crime rates and increase the demand of food delivery at home.

[8] We also show, in an extended version of this paper, that the introduction of platforms reduces violence against the person, destruction of property, and 'low skilled' property crimes (shoplifting and street robbery) but not 'high skilled' property crimes (burglaries and vehicle theft).

Our preferred explanation for the decline in crime is that food delivery platforms provide employment opportunities to demographic groups typically involved in such crimes, particularly young people, men, and low-skilled people. This suggests that gig jobs is a viable alternative to engaging in criminal and risky activities such as drug dealing.

Our paper contributes to several strands of the literature. First, it relates to investigations of the gig economy's influence on labor markets. Prior research on the gig economy has focused on the provision of flexibility (Mas & Pallais, 2017; Chen *et al.*, 2019). Digital platforms offer a novel alternative for marginalized and unemployed workers (Agrawal *et al.*, 2015; Huang *et al.*, 2020a; Laitenberger *et al.*, 2023). Guo *et al.* (2024) show how digital platforms provide opportunities for low-skilled workers. Burtch *et al.* (2018) show that the emergence of gig work influence entrepreneurial activity and provides job opportunities for the unemployed and underemployed. Huang *et al.* (2020b) show that unemployment in a given area is positively correlated with increased activity in online labor markets. Using the exogenous exit of a ride-sharing service, Shin *et al.* (2023) demonstrates that gig economy workers are likely to contribute to low-skilled roles in local restaurants. By contrast, in this paper we focus on the effect of online delivery platforms on employment of young men and crime rates.

Second, our paper contributes to the extensive literature on job opportunities and wage effects on criminal behaviors (Becker, 1968; Grogger, 1998; Machin & Meghir, 2004; Draca & Machin, 2015). We add to this research by focusing on job opportunities offered by the gig economy. Delivery work, characterized by low barriers to entry and minimal investment, improves the labor market prospects of young and low-skilled men. Given the disproportionate representation of this demographic in criminal statistics, an expansion in readily accessible gig jobs could lead to a reduction in crime rates.

Recent studies explore the relationship between ride-sharing services and the victimization rates of drivers and passengers. Dills & Mulholland (2018) show that introducing Uber-Driver apps does not significantly change the likelihood of victimization due to robbery, assault, or drunkenness. Conversely, Weber (2019) reports a 5% decrease in personal crime rates, albeit with no impact on other types of crime. Additionally, Weber (2019) notes only marginal evidence for a reduction in arrests related to driving under the influence and disorderly conduct. Our paper differs from Dills & Mulholland (2018); Weber (2019) by focusing on delivery work opportunities and workers' criminal behavior.

The paper is organized as follows. Section 2 presents our conceptual framework. Section 3 describes the context and shows descriptive statistics. Section 4 presents the empirical strategy. Section 5 presents the main results. The conclusion 6 follows.

2 Conceptual Framework

The purpose of this section is to offer a very simple conceptual framework.

Delivery Platforms — There are $z = \{1, \ldots, Z\}$ economic zones, each representing a distinct market of varying size. Online food delivery platforms evaluate these markets for potential entry based on the availability of restaurants (supply), consumers (demand), and riders. However, building supply, fostering demand, and recruiting riders is a time-consuming process that prevents simultaneous entry into all markets. Instead, platforms enter markets sequentially and prioritize them based on population size, as we will show empirically.

Riders — The key difference between food delivery platforms and other digital platforms, such as micro-tasking or homestays, is the role of the rider, usually use on a bicycle, who connects supply and demand. This gig job is characterized by low barriers to entry and low initial investment that particularly benefit a specific group g of workers: young, low-skilled, and often migrants.

Prior to platform entry — Let's focus on the group of workers g before a platform enters a given zone z. Those workers face limited employment opportunities, discrimination, and a Beckerian trade-off: accept legal, albeit low-wage and low-skill jobs, or venture into illegal activities that require low-skills, such as drug dealing or shoplifting.

The crime we model involves a drug street-level seller or a shoplifter, both offering average earnings somewhat above those of legitimate low-skilled job, but with considerable risk.[9]

[9]Using a unique dataset on the financial activities of a street-level drug gang, Levitt & Venkatesh (2000) show that earnings are highly skewed, with the average wage being somewhat above the legitimate labor market alternative. However, the substantial risks associated with drug selling far offset this small wage premium. The main economic incentive for low-level gang members is the potential to ascend the gang's hierarchy.

We note U_I the expected utility from working in the illegal activity:

$$U_I = \omega_I - pC,$$

where ω_I is the illegal wage activity (drug dealing), p the probability of getting caught, $C > 0$ the cost (monetary or otherwise, such as prison time) associated with getting caught. The utility from the low-skilled job is the minimum wage it offers, ω_L, plus some amenities or non-wage attributes, $a > 0$:

$$U_L = \omega_L + a.$$

Low-skilled jobs tend to offer fewer amenities a than high-skilled jobs due to hard working conditions, compounded by difficulties in finding a job, especially for first or second generation immigrant workers. Evidence shows that in France job candidates perceived as North African experience significant bias in hiring, particularly for low-skilled positions. For instance, assistant cooks applicants receive 45% fewer callbacks than those with French-sounding names, a gap that narrows by more than 20 percentage points for managerial positions.[10] Despite these relatively low amenities, we assume they exceed the amenities of illegal jobs, which we normalize to zero. This assumption is based on the greater regularity and predictability of income from legal employment, along with associated benefits such as health insurance, bank account, retirement plans, and overall more secure working conditions (see below).

An individual will choose the illegal job if its expected utility exceeds that of the low-skilled job, i.e., if

$$\omega_I > \omega_L + a + pC,$$

Individuals thus make their decisions based on a comparison of expected earnings and associated risks and amenities. We assume ω_I is a random variable and F represents the cumulative distribution of illegal earnings. ω_L is fixed and equal to the minimum wage.

The probability of choosing illegal work P_I is defined as:

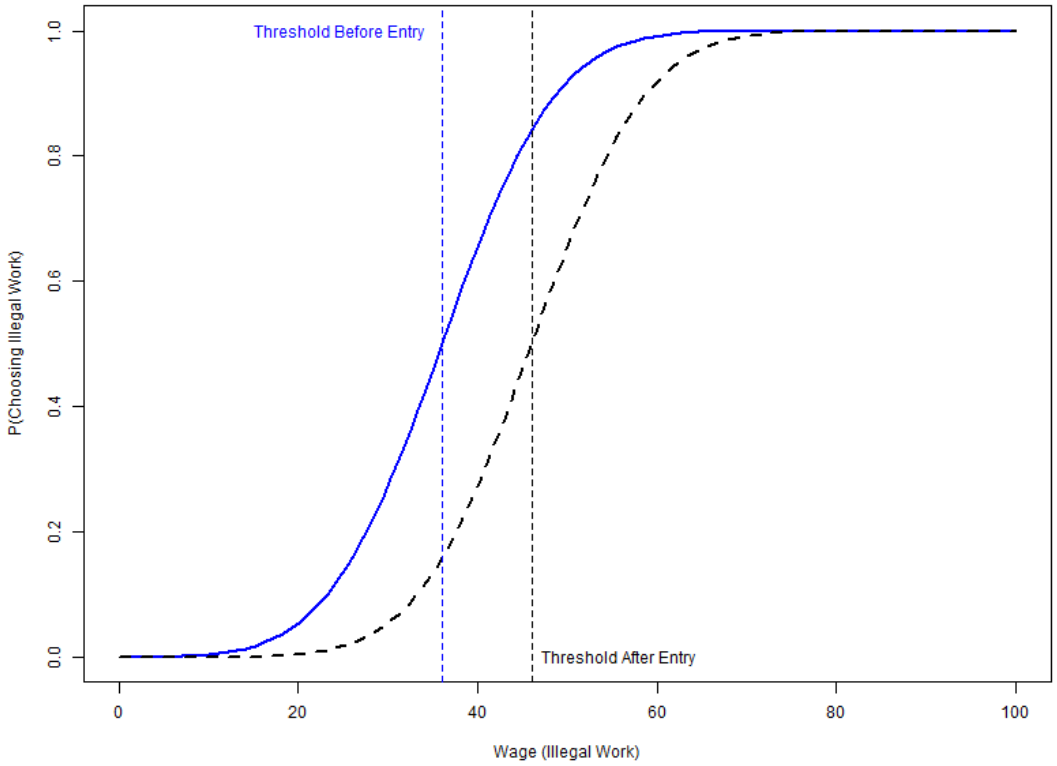
$$P_I = \mathbb{P}(\omega_I > \omega_L + a + pC) = 1 - F(\omega_L + a + pC),$$

[10] See IPP Policy Brief, #76, 2021: Discrimination in hiring people of supposedly North African origin: What lessons from a large-scale correspondence test?

which gives the likelihood that the potential earnings from illegal work exceed the value of legal earnings, plus any associated amenities and the risk (cost) of being caught.

After platform entry — The entry of a delivery platform in z improves the non-wage attributes of legal work, offering flexibility in scheduling and unbiased hiring practices. Registering to become a rider is free, requires no resume or application, and presents minimal barriers to entry (see Section 3.2). This improvement in job amenities increases the likelihood that individuals in group g will choose legal work over illegal work. This is illustrated in Figure 1.

Figure 1: Impact of Delivery Platforms on Illegal Work



Note: The solid blue curve represents the cumulative distribution before the entry of delivery platforms, and the dashed black curve represents the cumulative distribution after the entry. The vertical lines indicate the thresholds before (blue) and after (black) the entry of platforms.

Figure 1 shows the probability of choosing illegal work as a function of illegal wage. The solid blue curve represents the cumulative distribution before the entry of delivery platforms. The blue short dashed line represents the threshold wage at which the utility from legal work equals the utility from illegal work, adjusted for the amenities and risk and cost of being caught.

The rightward shift in the threshold wage after platform entry implies that a higher wage is now required to make illegal work more attractive relative to legal work. This is consistent with an increase in the amenities associated with legal work due to the entry of delivery platforms. Essentially, after the shock, the probability of opting for legal work rises at any given wage level compared to before the shock. This suggests that, for the same wage, individuals are more inclined towards legal work post-entry, highlighting an increase in the attractiveness or utility of legal employment.

This conceptual framework supports our empirical difference-in-differences approach, which compares pre- and post-entry periods of the platform in z with z' where the platform has not entered. We anticipate not only an increase in the number of riders in z but also an effect on illegal drug activities.

Figure 1 demonstrates the positive impact of delivery platforms on the labor market for low-skilled workers. By improving the non-wage attributes of legal jobs, digital platforms increase the opportunity cost of engaging in illegal activities. Consequently, fewer individuals choose illegal work, which can lead to a reduction in crime rates, especially in economically disadvantaged areas. This visual representation underscores the potential benefits of policies aimed at enhancing legal job opportunities for at-risk populations.

This conceptual framework underpins our empirical difference-in-differences approach, which compares pre- and post-entry periods of the platform in z with z' where the platform has not entered. We anticipate not only an increase in the number of riders in z but also an impact on illegal activities. Thus, if G is the total number of people in group g and $G_I = pG[1 - F(\omega_L + a + pC)$ is the number of individuals from g engaged in illegal activities (such as drug dealing or shoplifting), then G_I decreases as amenities increase, as indicated by $\frac{\partial G_I}{\partial a} < 0$.

Police and Criminal Organizations — Each zone is staffed with police officers based on its population size.[11] Police efforts are focused on crime monitoring and offender arrests. As a result, we would expect to see a decrease in number of arrests following the entry of digital delivery platforms, as more people opt for legal employment as riders. However, it is empirically challenging to determine whether new riders represents new entrants in the job market, potentially diverted from illegal activities, or individual tran-

[11] The correlation between the number of police officers and the population size at the police jurisdiction level is 0.93. See the Data section 3.3 for information on police officers.

sitioning from illegal to legal employment as riders. We argue that the increase in the number of riders encompasses both cases.

In the case of drugs, criminal organizations recruit members of group g for low-skill, high-risk tasks such as surveillance, supply missions, or street-level sales. While these roles are critical to the operations of these organizations, they expose workers to frequent police arrests.

Assessing the impact of reduced participation in illegal activities among group g is challenging. When we turn to the drug market, one possible outcome is the rationalization of the drug market. We find evidence that drug organizations, facing recruitment challenges, outsource specific functions, like product delivery, to specialized teams.[12] Organizations recruit among vulnerable youth living in the suburbs of major cities such as Lille, Paris, and Rennes, focusing on school dropouts and minors. In addition, traffickers employ people who do not reside at the sales locations, including women, to adapt to the tightening labor pool.

Another possible outcome is a change in prices as supply is disrupted by recruitment problems. However, based on data from the United Nations Office on Drugs and Crime, Appendix Figure 16 shows that street prices of heroin and cocaine are stable in France.[13]

3 Context and Data

3.1 Food Delivery Platforms

Platform Entry — Uber Eats and Deliveroo are the leading food delivery platforms in France.[14] Restaurants interested in partnering with Uber Eats and Deliveroo must register on their platforms and submit their application for approval. Upon approval, restaurants receive a digital tablet equipped with the platform's software to manage orders.[15] Consumers only need to download the platform's dedicated app and to provide a

[12] See 1999-2019: Changes in drug use and supply in France (in French) from the French Monitoring Centre for Drugs and Drug Addiction's (OFDT) and the TREND (*Tendances récentes et nouvelles drogues*) program.

[13] Unfortunately, our analysis is limited by data availability: we do not have access to drug prices at the local level. In addition, we lack information on the wages of drug dealers, which may have increased due to a reduced labor supply.

[14] Competitors, with a smaller market share, include Stuart, Frichti, Foodora (until 2018), Nestor, Glovo and Yper. Notably, JustEat employs workers under formal contracts.

[15] Restaurants appear on the platform only after owners complete a training course on software usage.

few details such as their name, email, debit card number, and a delivery address to use the service. There are no administrative barriers to entry for platforms, as they are not required to comply with administrative procedures.

We exploit the staggered entry of digital food delivery platforms across France. For instance, Uber Eats launched in 2015 in Paris,[16] followed by Lyon in 2016, whereas Deliveroo entered in 2015 in Paris and 4 majors cities (Bordeaux, Lille, Nantes, and Lyon), and then in ten major cities in 2016.[17] Both platforms have gradually expanded by targeting the most densely populated cities, called "reference markets," from which they serve nearby and less densely populated urban and rural areas. As of 2019, Uber Eats and Deliveroo are deployed in 2,114 cities or reference markets, covering most of the country and representing 57% of the French population (see Appendix Figure 12). We describe in Appendix A how we reconstructed the timeline of platform launches in the reference markets based on regional and national media outlets, as well as platform websites.

Determinants of Platform Entry — The potential endogeneity of platform entry is a major concern, as it may be correlated with the socio-economic characteristics of a particular reference market. Table 1 displays our survival analysis, based on Uber Eats, which is used for its extensive geographic coverage, to examine the key factors influencing the timing of market entry.[18] In the Cox regression model, the response variable is the time to entry of Uber Eats, starting with its launch in Paris in 2015. Predictors include the log-transformed population, median income in levels,[19] unemployment rate, educational attainment categories, and immigrant share in these reference markets.

The Cox estimates show that the log of population size significantly predicts Uber Eats' entry into French cities, with a coefficient of 1.292 (p-value < 0.01). This indicates that a 1% increase in population size corresponds to a 3.64-fold increase in the likelihood of Uber Eats' market entry. Delivery platforms are more likely to enter in larger cities. Other socio-demographic factors have no significant effect on the timing of entry. These findings support the platforms' reference market approach, which allows them to serve densely populated areas and surrounding rural or less populated neighborhoods.

[16] Uber Eats first tested its food delivery service in a few neighborhoods in Paris in 2014.

[17] Since their launch, Uber Eats and Deliveroo have expanded their services to include grocery delivery through partnerships with retailers such as Carrefour.

[18] These results are also depicted graphically with survival curves in Appendix E.

[19] Using logs does not affect the results, which are available upon request.

Table 1: Determinants of Uber Eats Entry Timing in French Cities

Dependent Variable: Probability of Uber Eats Entry	
log(Population)	1.292***
	(0.107)
Median Income	0.000
	(0.000)
Unemployment (%)	5.908
	(3.919)
High-School Diploma (%)	-0.313
	(3.991)
No Diploma (%)	-2.670
	(1.750)
Immigrants (%)	0.860
	(1.284)

Notes: Cox Proportional Hazard model depicting the influence of demographic and socioeconomic factors on the timing of Uber Eats' market entry into French cities. 2,674 observations on Reference Markets at year t. Standard errors in parenthesis with significance levels: * <0.1, ** <0.05, *** <0.01.

3.2 Riders

Requirements and Earnings — To work with Uber Eats or Deliveroo, individuals must meet certain requirements. These include being at least 18 years old and having a valid ID, such as a European Union passport, a residence permit, or a work permit for asylum seekers. Workers must also register as independent contractors or self-employed, which is free (see below).

An additional requirement is that individuals must not have a serious criminal record, such as a prison sentence of more than two years (*Casier Judiciaire* level B3). Minor convictions, such as for violence or theft (*Casier Judiciaire* level B2), will not prevent a person from registering as a rider, although they may restrict access to many other jobs (e.g., car-sharing driver, work with children, security jobs, and certain public sector jobs).

Legal requirements create barriers for undocumented migrants who wish to work as riders (including asylum seekers without work permit). This situation has led some registered riders to illicitly subcontract their work by renting their accounts to undocumented or underage workers for a fee. Platforms have taken steps to address these practices. For example, Uber Eats does not tolerate illegal or underage employment and employs 100

people in France to conduct spot checks,[20] which led to the suspension of 2,500 accounts in 2019 for illegal rental practices.[21] Measuring the number of unregistered riders is challenging. However, if it correlates with the number of registered riders in a location, we can confidently control for the potential underestimation bias of the total number of riders.

Once approved by the platform, riders can begin deliveries. In France, the most popular and cheapest means of delivery is by bicycle, which can be purchased for between 100 and 300 euros.[22] Riders must also have a smartphone and purchase a dedicated branded bag to deliver the food.

Delivery work offers notable flexibility, allowing riders to freely choose their days and hours of work, with no minimum or maximum hour requirements. When an order is placed by the platform, the rider receives details about the order and can decline it. Earnings per delivery vary based on several factors, including the city (with higher rates in Paris), the number of active riders, travel distance, peak hour surcharges, weather conditions, and customer tips. On average, workers earn slightly more per hour than the minimum hourly wage (Daugareilh, 2022). In 2018, Uber Eats reported that riders in France earned between €10 to €15 per hour during peak times, while Deliveroo reported an average hourly earning of €13.[23]

Demographics — The INSEE database on self-employed entities provides the names and genders of the riders (see below). Over 95% of the riders are men (see Appendix Table 3). The list of name allows us to identify riders' age group and ethnicity. Figure 2 displays a word cloud of names of the riders in our dataset.

Appendix Table 4 shows that most riders are under 40 years old. Additionally, Table 5 suggests that the majority of riders have foreign first names. Consequently, typical riders are young men, and many have immigrant backgrounds.[24]

[20] https://www.nytimes.com/2019/06/16/business/uber-eats-deliveroo-glovo-migrants.html

[21] https://www.capital.fr/entreprises-marches/uber-eats-la-plateforme-deconnecte-2500-comptes-frauduleux-de-livreurs-1445488

[22] Under French law, using a scooter or car involves additional requirements. Riders must complete 102 hours of training and pass an exam to obtain a transport license, which costs about €500. Additionally, they must cover related expenses, including insurance, fuel and others. In the UK, riders can access the rider kit for a fee of GBP 150, which is deducted from their first wage (see "The experiences of those in the gig economy".

[23] https://www.nytimes.com/2019/06/16/business/uber-eats-deliveroo-glovo-migrants.html

[24] See also the ISPOS survey of Uber Eats.

Figure 2: Word Cloud of Riders' Names



Notes: From the INSEE database on self-employed entities.

Number of Riders — Riders must register as self-employed entities to work with delivery platforms. The full list of registered companies, including self-employed individuals, is recorded in the administrative dataset SIRENE. This dataset provides information on professional activities creation and closure dates, ZIP code locations, sectors of activity, and legal status[25] Riders are recorded in the 'Other postal and rider activities' category of the French National Institute of Statistics (INSEE).[26] We compute the number of active riders in a given municipality and year by tracking their dates of business creation and closure, assuming that riders use their home address for registration purposes.

Figure 3 illustrates the significant growth in riders since the delivery platforms launched in 2015, from a few thousand to more than 100,000 in 2019.[27]

We supplement our data with INSEE's annual city-level statistics on population, unemployment, income, age distribution, educational attainment, and immigrant demographics. Correlating the number of registered riders with these variables reveals a strong positive association with population size and the proportion of immigrants, and a negative correlation with median income (see Table 2). These patterns suggest that food delivery platforms primarily provide employment opportunities to lower socio-economic classes, including migrants.[28]

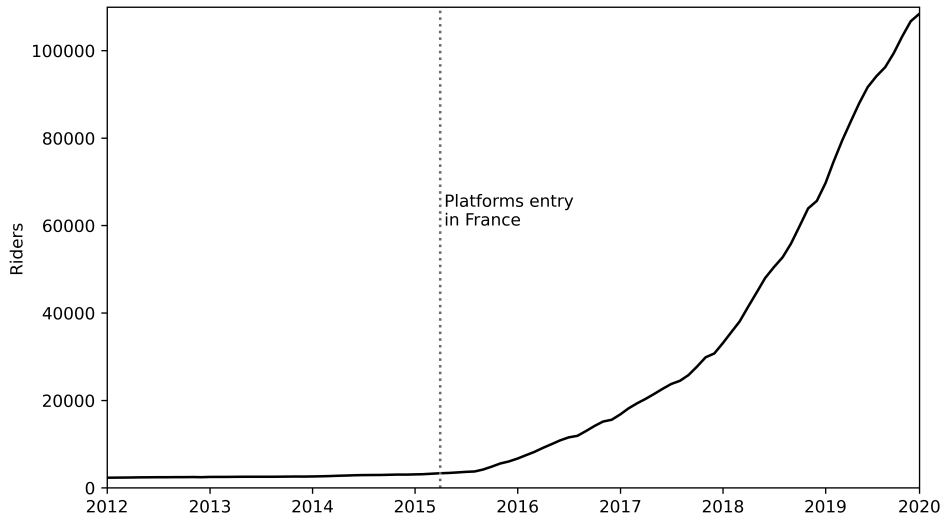
[25] See the SIRENE database.

[26] The category "Other postal and rider activities" is referenced with the code "53.20Z" in the INSEE "NAF Rév2" classification of economic activities.

[27] Note that these figures also include self-employed workers in the non-food delivery sector, with the large exception of most Amazon drivers, who are employed by the company.

[28] Appendix Figure 13 supports this finding, showing the distribution of riders relative to demographics in Paris (dashed area) and surrounding municipalities in 2019. The maps show a higher concentration of riders per inhabitant in the northern municipalities, which tend to have lower median incomes, lower education levels, and higher unemployment rates.

Figure 3: Number of Riders in France



Notes: The figure shows the growth of riders in France based on data from the SIRENE administrative dataset, which tracks self-employed entities in the 'Other postal and rider activities' category. The vertical dashed line represents the entry of delivery platforms in 2015.

Table 2: Matrix Correlation

	Delivery Workers†	Population†	Median Income†	Un-employment	Share Immigrants	No Diploma	High-School Diploma
Population†	0.724**						
Median Income†	-0.251**	-0.308**					
Unemployment	0.335**	0.443**	-0.848**				
Share Immigrants	0.607**	0.243*	-0.095	0.117			
No Diploma	0.110	0.109	-0.885**	0.76**	0.103		
High-School Diploma	-0.216*	-0.162*	-0.597**	0.288**	-0.201*	0.605**	
Share Renters	0.605**	0.584**	-0.525**	0.609**	0.431**	0.312**	-0.127

† indicates that the variable is in logarithm. The sample is restricted to cities where a platform has entered. In addition, we restrict the sample to the year after the platform entry in the city to avoid capturing variations in the number of riders caused by differences in the relative time since entry. Pearson test significance: * <0.05, ** <0.01 .

Time Period Studied— We limit our analysis from 2012 to 2019 to avoid any bias related to the COVID-19 pandemic. First, home lockdowns significantly reduced crime rates, which could distort our findings. Second, during the pandemic, the surge in demand for delivery services led to an increase in the number of delivery workers, making them ubiquitous. This increased visibility and prevalence of delivery personnel were exploited by drug cartels, which began using parallel delivery systems to distribute drugs. While this phenomenon existed sporadically before the pandemic, it has become much more widespread since.[29] Limiting our analysis to the pre-pandemic period helps ensure that our results are not affected by these pandemic-related biases.

[29]See Interpol report on dealers using food delivery services to transport drugs during COVID-19 lockdowns.

3.3 Police Jurisdictions and Crime

For historical reasons, law enforcement, public safety, and crime prevention responsibilities are ensured by two distinct entities called "Police " and "Gendarmerie". Although they share an identical code of ethics and perform similar missions, they operate in separate jurisdictions.[30] The Police focuses on maintaining law and order in urban areas, while the Gendarmerie is deployed in rural areas and smaller towns (see Appendix Figure 14 for law enforcement areas of Police and Gendarmerie jurisdictions). For simplicity, and given their similar law enforcement roles, we refer to Police and Gendarmerie as 'urban police' and 'regional police,' respectively.

We measure crime rates at the local level using administrative data from official police authorities.[31] The data aggregate "facts" annually at the level of law enforcement jurisdictions since 2012. A fact is an incident recorded on police initiative or following a complaint, a report, a witness statement, a flagrant offense, or a denunciation. We supplement our crime data with the number of police officers by jurisdiction.[32]

Between 2012 and 2019, some jurisdictions underwent administrative mergers. To maintain a consistent panel structure, we adjust jurisdictions to the most aggregated delineation observed in the dataset (see Appendix C.2 for more details).

One variable of interest is drug-related crime, an income-generating offense that can serve as a substitute for formal employment (see Section 2). Urban and regional police document and classify crimes, since 1972, with a detailed system known as "État 4001". Four types of drug offenses are recorded: (1) Use, (2) Possession or dealing (also referred to as "Drug use/resale"), (3) Trafficking and resale without use of narcotics, and (4) Other drug offenses.

We focus on the first two categories of drug offenses because trafficking includes the production, importation, or exportation of narcotics, which involves more high-level drug members, while other drug-related offenses include miscellaneous offenses such as drug advertising. Drug use in France is prohibited and punishable by imprisonment and fines, without distinction of product, as in some countries (e.g. the United Kingdom), and is covered by the Public Health Code. Drug possession or drug dealing (two terms we

[30] They also fall under different ministries. The Police operates under the Ministry of the Interior and the Gendarmerie under the Ministry of Defense.

[31] The dataset is publicly available on the INSEE website.

[32] This dateset maintained by the French government is publicly disclosed by a journalist on the website http://lepanierasalade.fr/effectifs/.

use interchangeably) is covered by the Penal Code and is punishable by imprisonment. In 2020, most of convicted individuals were consumers (131,385, or 81%), far ahead of those involved in possession (14,844 people, or 9%), trafficking (14,791, or 9%), or other drug-related offenses (1,769, or 1%).[33]

The disaggregated classification of (drug) crime is useful but potentially subject to distortions and subjective interpretation by police officers. For example, drug dealers have an incentive to carry small amounts of drugs in order to be classified as users rather than dealers. Different officers might classify the same offense differently. Additionally, in 2012, the classification system was changed all at once for regional police but only gradually for urban police. This gradual update means that urban police stations did not consistently use the same disaggregated classification of offenses until at least 2016.[34] To address this issue, we use an aggregate *drug-crime* variable, which includes all procedures and arrests related to possession, purchase, use, cultivation, production, trafficking, or advertisement of illicit drugs. We will only use the disaggregated classification at the regional police level.

4 Identification Strategy and Empirical Results

4.1 Staggered Difference-in-Differences

The rollout of the delivery platforms in z allows us to implement a staggered difference-in-differences (DiD) method. As long as the parallel trend assumption is satisfied and anticipation effects are absent, this method provides an unbiased estimate of the impact of platform entry on crime and employment.

The entry of delivery platforms in z can impact crime rates through two mechanisms. First, individuals involved into illegal activities can decide to work as riders when a delivery platform enters the market. Second, individuals outside the labor force or newcomers to the labor market, who are not involved in any criminal activities, may be deterred from entering the illegal activities due to the availability of delivery jobs. Both mechanisms support a contemporaneous treatment effect, as individuals face the Beckerian trade-off as soon as a platform enters z. However, the effects might be delayed for several reasons.

[33] See https://www.ofdt.fr/sites/ofdt/files/2024-06/eftxio2b4 and Appendix Figure 15.

[34] For more details, see Appendix C.1 and a methodological note from the Ministry of Home Affairs (*Ministère de l'Intérieur*).

First, some individual involved in criminal activities may switch to delivery work later than others. Second, a continuous influx of newcomers, who might otherwise have engaged in drug crimes, may choose delivery jobs instead. Additionally, platforms may initially limit the number of new riders when the demand for food delivery orders in z is low. This limit decreases as new restaurants or consumers join the platform. Consequently, one might expect an increasing effect over time, corresponding to the growth in supply and demand–a typical network effect of digital platforms.

More specifically, we estimate the following specification:

$$\mathrm{Y}_{zt} = \alpha_z + \lambda_t + \sum_{\tau=-9}^{4} \beta_\tau \mathrm{Entry}_{z,t}^{\tau} + \epsilon_{z,t}, \tag{1}$$

where Y_{zt} indicates three outcome variables *riders*, *employment* or *crime* in area z in year t. $\mathrm{Entry}_{zt}^{\tau}$ is a set of indicator variables that take value one if the delivery platform entry was τ years away. α_z and λ_t are area and year fixed-effects, respectively. Finally, ϵ_{zt} is the error term that is assumed to be i.i.d.

Assuming that the crime rate would have followed parallel trends across different areas in the absence of platform entry, that the entry effect was not anticipated, and that the average treatment effect (ATT) is homogeneous across areas and years, β identifies the ATT of the delivery platform entry on crime.

One possible concern is that unobserved differences in area characteristics may affect crime trends. For example, areas with higher population densities may experience greater police efforts to reduce crime. In addition, area characteristics may evolve differently after entry. For instance, a platform entry may attract low-skilled workers or migrants, which could affect both ridership and crime rates. To address these concerns, we include area fixed effects (α_z) to control for size effects. Then, as a robustness check, we also control for time-varying area characteristics, such as population or migration rates.

Although the Two-Way Fixed Effect (TWFE) is the workhorse model for staggered treatment estimation, it has been shown to be inconsistent when treatment effects are heterogeneous across treated groups and/or time. We address this problem by using the De Chaisemartin & d'Haultfoeuille (2020) and Callaway & Sant'Anna (2021) estimators, which relax the homogeneity assumption for treatment effects.

The DiD method captures the *extensive margin*, i.e., the average impact of the platform entry on crime. Since platform entry increases the number of riders, we can also estimate

the *intensive margin* effect, which measures the impact based on the intensity of riders. However, estimating this policy-relevant effect requires a different identification strategy to address the potential endogeneity of the number of riders. Appendix G presents the IV approach and the estimates.

4.2 Treated Areas and Spillover Effects

The police jurisdiction is the most disaggregated spatial unit for recording crime.[35] Each municipality belongs to only one jurisdiction, but a jurisdiction can cover more than one municipality. Our data include 681 police jurisdictions, representing an average of 50 municipalities.[36] An empirical challenge is that all municipalities within a jurisdiction may not be treated at the same time. A jurisdiction is designated as treated in the year its first municipality is treated, typically aligning with the entry into the most populous municipality, which platforms target as their primary reference market.

Another empirical challenge in estimating the impact of entry on crime is that riders may work or potentially engage in criminal activity outside their jurisdiction of residence. To capture the spillover effects that increasing the number of riders in one city may have on another, we use a larger geographic and economic area: commuting zones. This comprehensive spatial area encompasses riders, restaurants, and consumers to accurately assess how delivery work affects crime rates. The administrative commuting zone is defined by the national statistical office (INSEE) based on the significant proportion of individuals who both live and work within them.[37] Our data cover 280 commuting zones, which represent on average 123 municipalities. Aggregating crime data from police jurisdictions to commuting zones is challenging, given that a single jurisdiction may span multiple commuting zones. In this particular case, we allocate crime figures proportionally, based on the percentage of the jurisdiction's population covered by each commuting zone. Furthermore, we define the entry date of a platform in an commuting zone as the earliest entry date among all municipalities in the commuting zone, following the same logic as above: the most populous municipality in the area is treated first.

[35] For an illustration of the geographical levels used in our analysis, see Appendix Figure 17.

[36] It should be noted that in France, 88% of municipalities are rural or small, with fewer than 2,000 inhabitants.

[37] Commuting zones (or '*zones d'emploi*') are defined through an algorithm with two objectives: first, that at least 70% of stable active workers reside and are employed within the same zone, and second, that each area reaches 25,000 active workers (see the INSEE methodology) for further information.

The estimates using commuting zones control for spillover effects because they are delineated to include areas where the majority of residents both live and work. However, many commuting zones include both regional and urban police jurisdictions, and the disaggregated crime statistics from these two jurisdictions are not always comparable (see Section 3.3 on crime). Consequently, we focus on police jurisdictions as our main spatial unit of analysis and use commuting zones to check the robustness of our results to aggregate crime measures.

4.3 Police Jurisdictions: Urban & Regional Differences

Two institutions carry out law enforcement in France: Urban and regional police (see section 3.3). These institutions and their jurisdictions present key differences for the analysis. By the end of 2019, Uber Eats and Deliveroo were operating in 17 out of 341 regional police jurisdictions, compared to 234 out of 340 urban police jurisdictions. This difference reflects the platforms' tendency to enter urban areas first but does not mean that regional jurisdictions are not treated. To capture the spillover effects of platform entry, we adjust our approach to defining treated jurisdictions. Urban police jurisdictions are treated when a platform first enters a city within their jurisdiction. In contrast, we consider a regional police jurisdiction to be treated when a platform first enters within 15 kilometers of its border. This 15 km criterion is conservative and consistent with the median commuting distance for rural residents.[38] As a sanity check, we test whether our definitions of treated jurisdictions are appropriate using the number of riders. The underlying hypothesis is that the number of riders should increase only with platform entry. Therefore, when estimating Appendix equation 2, with the ratio of riders to population as the dependent variable, we do not expect pre-trends in the number of riders for accurately defined treated units. In contrast, if some units are incorrectly considered as untreated or are treated too late, a negative pre-trend would emerge, indicated by an increase in riders within the supposed control group.

Another previously mentioned difference between the two jurisdictions stems from a change in record-keeping by urban police. As a result, we analyze the impact of delivery jobs on drug offenses separately for both jurisdictions. This approach ensures that our

[38] In 2019, the median commuting distance by car from home to workplace for those living in rural areas was 13 kilometers, according to INSEE statistics. We also use a 10 km distance buffer.

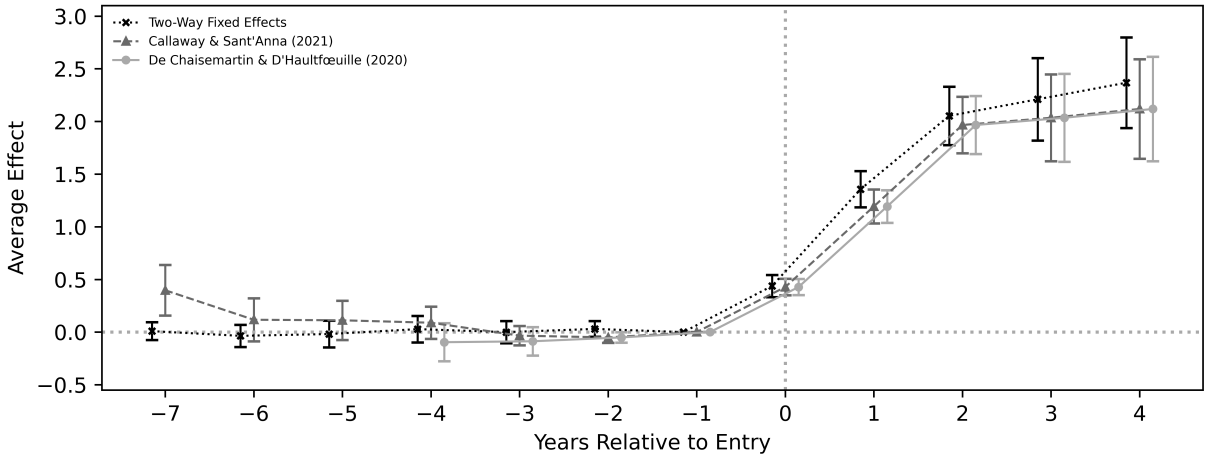
results are not affected by data inconsistencies, which only affect the Urban Police's breakdown of aggregate statistics into different drug crime categories.

5 Results on Police Jurisdictions

5.1 Impact on the Number of Riders

Using equation 1, Figure 4 presents event-study plots of platform entry on riders per capita in *urban* police jurisdictions. Estimates are consistent with the parallel trends and no anticipation assumptions. Notably, there is a significant increase in riders per capita only after platform entry. Overall, the estimates show a significant increase in riders per capita within four years after the introduction of a food delivery platform. This is consistent with the raw data presented in Figure 3.

Figure 4: Food Delivery Platform Entry and Riders in Urban Police jurisdictions

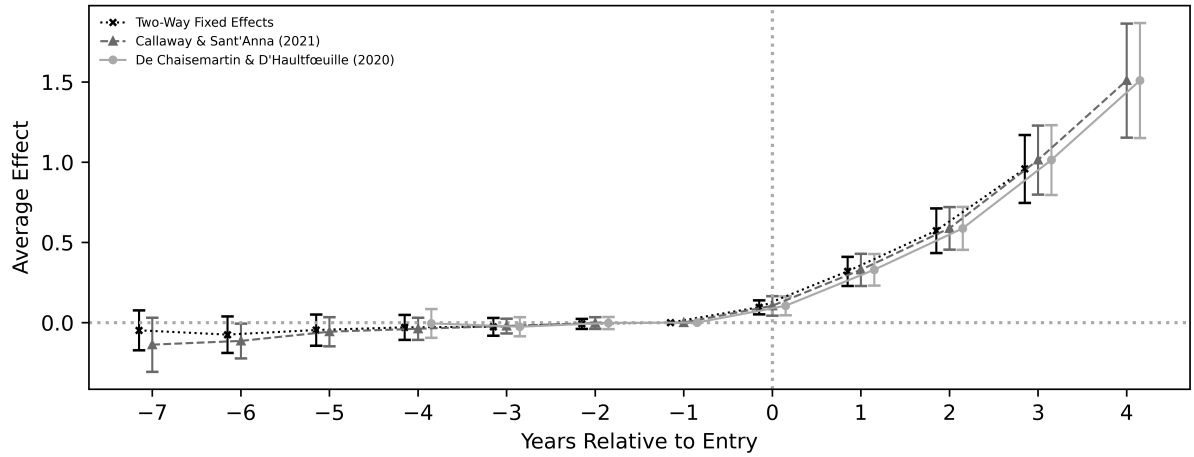


Notes: Event-study estimates using *the logarithm of riders per capita* as the dependent variable. The sample is restricted to urban police jurisdictions only. Estimators used are: TWFE-OLS, Callaway & Sant'Anna (2021) and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals, with standard errors clustered at the jurisdiction level.

Figure 5 shows event-study plots of food delivery platform entry on riders per capita in *regional* police jurisdictions. Again, pre-treatment estimates appear to be consistent with the parallel trends and no anticipation assumptions. The results indicate that the entry of food delivery platforms leads to a 380% increase in the number of riders per capita after four years.

Overall, our definitions of treated units are well defined as the parallel trends and no anticipation assumptions are verified in both cases. Appendix Figure 25a overlays the

Figure 5: Food Delivery Platform Entry and Riders in Regional Police Jurisdictions



Notes: Event-study estimates, *log riders per capita* is the dependent variable. The sample is restricted to regional police jurisdictions only. We use the following estimators: TWFE-OLS, Callaway & Sant'Anna (2021) and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. Standard errors clustered at the jurisdiction level.

same estimation as regional police jurisdictions, but instead uses a 10-kilometer distance from the jurisdiction boundary. In this scenario, the common trends assumption is not verified. The negative pre-trend suggests that some jurisdictions are considered as treated too late. This is resolved with a distance buffer of 15 kilometers.

5.2 Impact on Labor Outcomes and Social Welfare

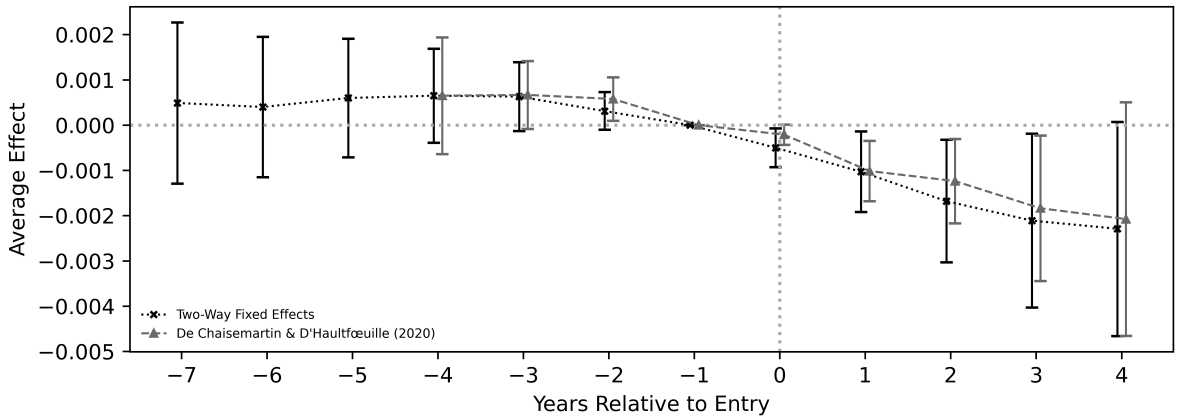
Unemployment — Figure 6 overlays the event-study plots of platform entry on unemployment rate. Panel A shows the results for regional jurisdictions using the 15 km buffer, while Panel B shows the results for urban jurisdictions. The estimates include the population aged between 15 and 64 as a control to correct for pre-trends. However, including this covariate makes the Callaway & Sant'Anna (2021) method unreliable, because of its matching strategy on covariates in the pre-treatment period. Table 1 shows that early entries of food delivery platforms are highly positively correlated with city population size, making it difficult to find comparable control units for matching. Consequently, the reported standard errors with Callaway & Sant'Anna (2021) are unreliable, especially for early treated units. In contrast, De Chaisemartin & d'Haultfoeuille (2020) control for covariates by including residuals from regressions of the first-difference of the outcome on the first-difference of the controls and time fixed effects, thus avoiding the matching method. Therefore, in this section, we always present results using TWFE-OLS

and De Chaisemartin & d'Haultfoeuille (2020), controlling for population aged between 15 and 64.

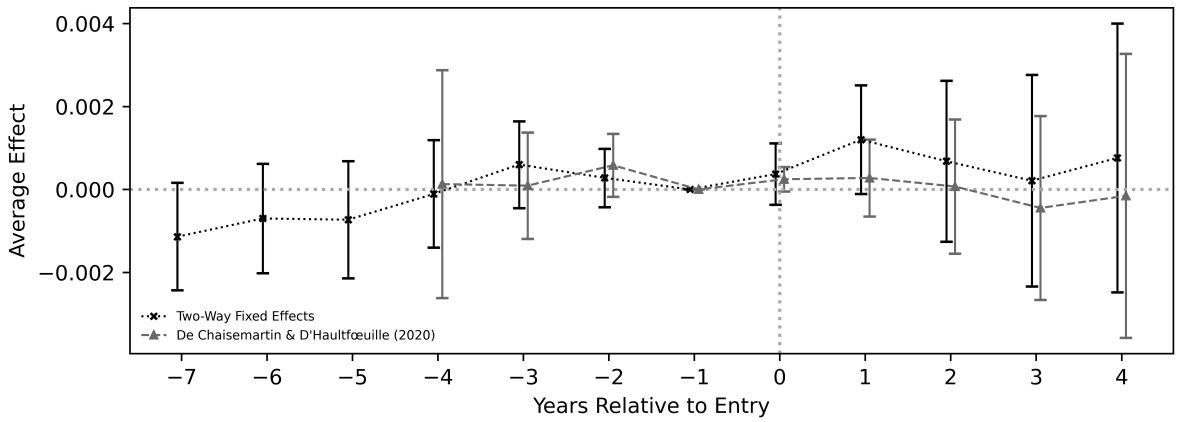
For both regional and urban jurisdictions, pre-treatment estimates are consistent with the parallel trends and no anticipation assumptions. However, estimates suggest different effects of platform entry on the unemployment rate in these jurisdictions. For context, the pre-treatment unemployment rate is lower in regional jurisdictions (8.2%) than in urban jurisdictions (10.8%). While platform entry reduces the unemployment rate by 0.21 percentage points (p.p.) after four years in regional jurisdictions, there is no significant effect in urban jurisdictions. The reason may be that the number of jobs offered by delivery platforms in urban areas is not sufficient to affect unemployment in these jurisdictions.

Figure 6: Unemployment Rate in Police Jurisdictions

A. Regional Jurisdictions



B. Urban Jurisdictions



Notes: Event-study estimates as defined in equation 1 with the *unemployment rate* as the dependent variable. Methods used are: TWFE-OLS and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. The population aged between 15 to 64 is included as a control. Standard errors clustered at the jurisdiction level.

Inactive Persons — Figure 7 presents event-study plots of platform entry on the rate of people outside the labor force. An individual is considered as inactive if she is of working age, has no formal employment and is not actively seeking for a job. Panel A shows results for regional jurisdictions using the 15km buffer, while Panel B shows results for urban jurisdictions. For both regional and urban jurisdictions, pre-treatment estimates are consistent with the parallel trends and no anticipation assumptions. Post-treatment estimates indicate a decrease in the inactivity rate in both types of jurisdictions. After four years, platform entry decreases the inactivity rate by 0.37 p.p. in regional jurisdictions and by 0.85 p.p. in urban jurisdictions. For context, the average inactivity rate before treatment approximates 27% in regional jurisdictions and 24% in urban jurisdictions. The findings indicate that platform entry has a larger effect on inactivity rate than unemployment rate. These findings suggest that new delivery job opportunities mainly benefit individuals outside the labor market, consistent with the conceptual framework discussed in Section 2.

Social Welfare for the Unemployed — Figure 8 presents event-study plots of platform entry on the share of social benefits for statutory minimum over household disposable income. This financial aid is a sub-category of social benefits.[39,40] Eligibility depends on financial resources or specific contexts such as disability. This subcategory includes 10 types of aid: the active solidarity income (*RSA*) and the allowance for asylum seekers (ADA).[41] These social benefits are specifically designed for low-income households and disabled individuals. In 2019, 75% of individuals receiving aids for statutory minimum live with less than €940 per month.[42]

Panel A shows the results for regional jurisdictions a 15km buffer, while Panel B shows the results for urban jurisdictions. For context, the average share of these benefits before treatment was 1.6% in regional jurisdictions and 2.6% in urban jurisdictions. For

[39]Social benefits are public transfers, in cash or in kind, to individuals or families for protection against various risks. Social benefits include transfers for 6 major risk categories: old age and survival, health, maternity-family, job loss, housing difficulties, and poverty and social exclusion. See https://www.insee.fr/en/metadonnees/definition/c1562 for further details.

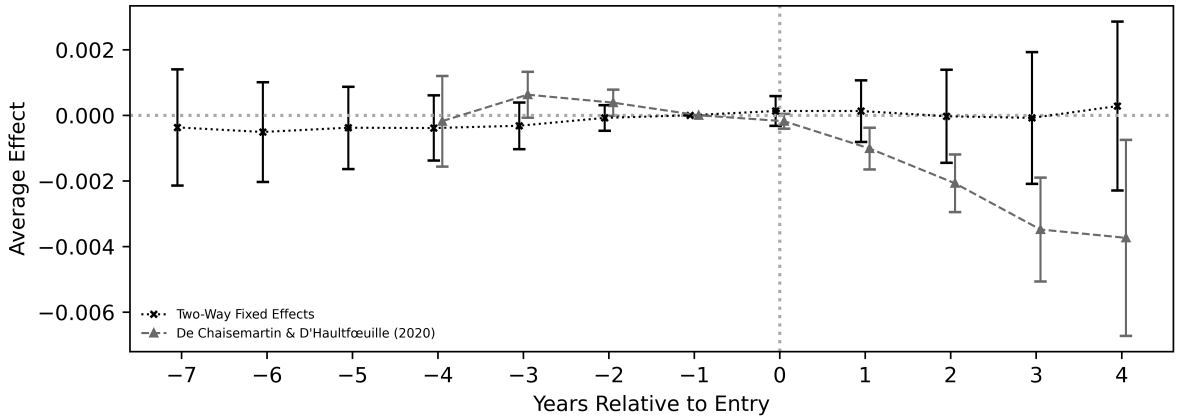
[40]Results on the overall social benefits are presented in Appendix F.

[41]The RSA is an allowance that supplements the household's initial income to reach a guaranteed income level. The guaranteed income level in 2019 was €559.74 for a single household. This corresponds to 46.5% of the tax-free minimum wage in force at that time. See https://www.insee.fr/fr/statistiques/2411049 for the list (in French) of allowances included in this category.

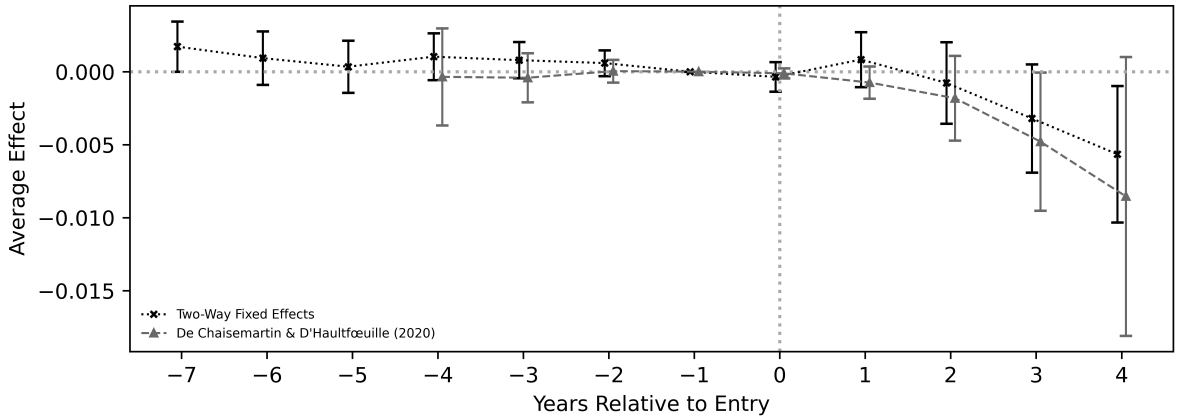
[42]See https://drees.solidarites-sante.gouv.fr/publications-communique-de-presse-documents-de-reference/panoramas-de-la-drees/minima-sociaux-et-0 in French.

Figure 7: Inactivity Rate in Police Jurisdictions

A. Regional Jurisdictions



B. Urban Jurisdictions



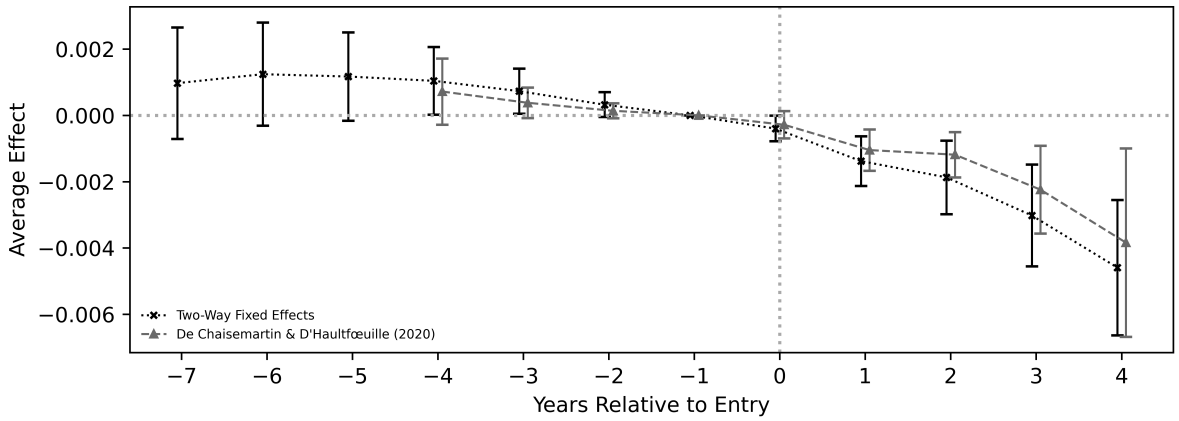
Notes: Event-study estimates as defined in equation 1 with*Inactivity rate* as the dependent variable. Methods used are: TWFE-OLS and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. The population from 15 to 64 years old is included as a control. Standard errors clustered at the jurisdiction level.

both regional and urban jurisdictions, pre-treatment estimates are consistent with the parallel trends and no anticipation assumptions. Post-treatment estimates indicate that platform entry decreases the share of financial aids for statutory minimum for both types of jurisdictions. Post-treatment estimates indicate that platform entry decreases the share of statutory minimum social benefits by 0.38 p.p. in regional jurisdictions and by 0.66 p.p. in urban jurisdictions after four years. These results indicate that much of the observed decrease in social benefits over household incomes in Appendix Figure 24 is due to reduced statutory minimum benefits. The findings also imply that the increase in employment opportunities through food delivery platforms increases earnings, reducing eligibility and the amount of benefits received. In addition, the results suggest that low-

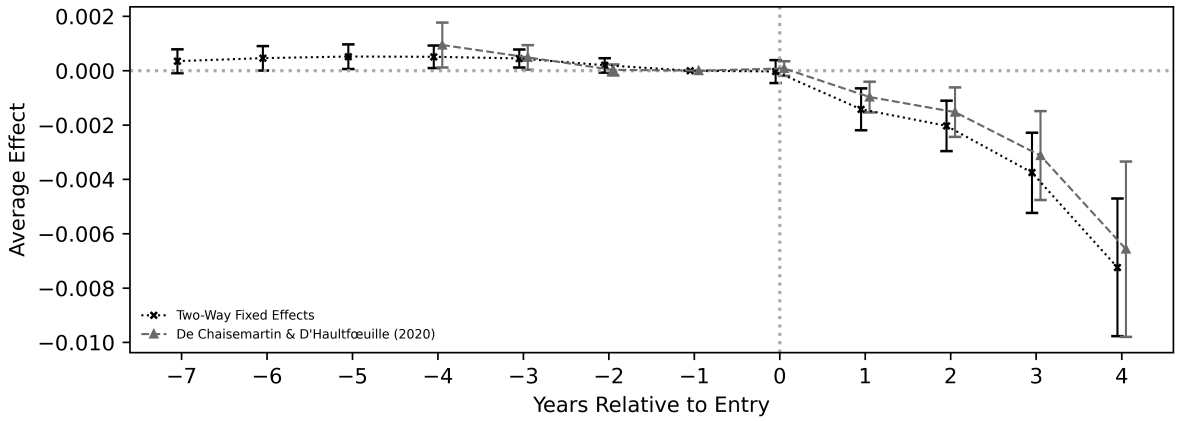
income individuals, particularly those with no legal income, benefit from increased food delivery job opportunities.

Figure 8: Share of Social Benefits for Statutory Minimum in Police Jurisdictions

A. Regional Jurisdictions



B. Urban Jurisdictions



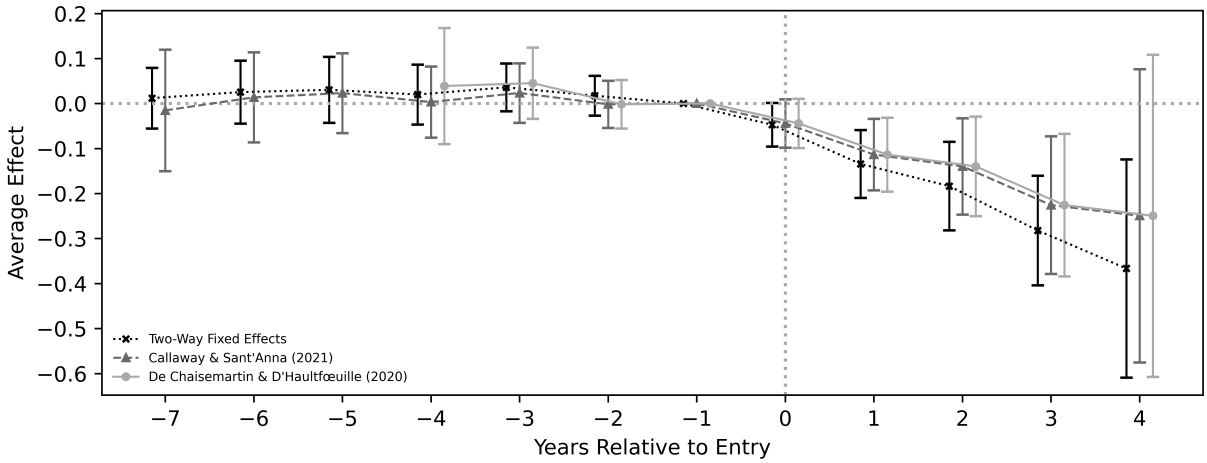
Notes: Event-study estimates as defined in equation 1 with *the share of social benefits for statutory minimum over household income* as the dependent variable. Methods used are: TWFE-OLS and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. The population from 15 to 64 years old is included as a control. Standard errors clustered at the jurisdiction level.

5.3 Drug Crimes in Police Jurisdictions

Figure 9 displays event-study plots of platform entry on drug crime rates for *urban* police jurisdictions. The estimates correspond to β in equation 1. The pre-treatment periods indicate that the common trends assumption is verified. The post-treatment periods show a decrease in drug crime rate after a platform entry. In addition, the effect is dynamic as it increases over time. This result follows the increase in riders over years

and is consistent with the impact of platform entry on unemployment, inactivity and social benefits. Accounting for treatment heterogeneity, the estimates indicate a 22.1% reduction in drug crime rates over a period of 4 years following the introduction of a food delivery platform.

Figure 9: Food Delivery Platform Entry and Drug Crime in Urban Police Jurisdictions



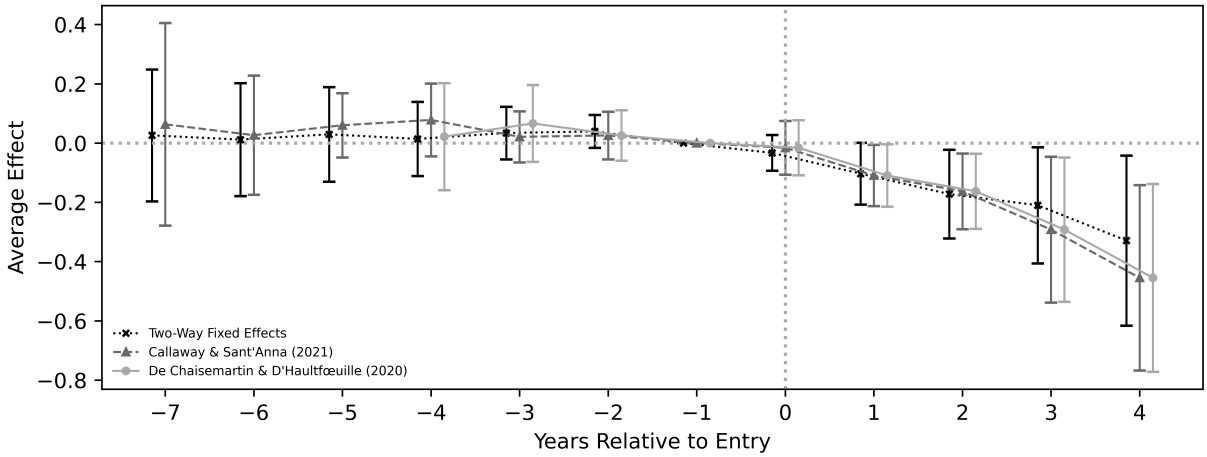
Notes: This figure displays the event-study estimates using the *logarithm of the drug crime rate* as the dependent variable. The sample is restricted to urban police jurisdictions only. Estimators used are the followings: TWFE-OLS, Callaway & Sant'Anna (2021) and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. Standard errors clustered at the jurisdiction level.

Figure 10 shows the event-study estimates for *regional* police jurisdictions. Again, the pre-treatment periods indicate that the common trends assumption is verified and do not exhibit anticipation effects. The post-treatment estimates suggest that a food delivery platform entry reduces the drug crime rate, with an increasing effect over years. Accounting for treatment heterogeneity, the estimates indicate a reduction in drug crime rates by 36.5% over a period of 4 years following the introduction of a food delivery platform. In addition, Appendix Figure 26 presents the same event-study at the commuting zone level. The results are consistent, as the entry of a food delivery platform reduces the drug crime rate in that area.

5.4 Decomposition by Type of Drug Crimes

The expansion of the gig economy has created new job opportunities for low-wage, low-skilled workers and reduced barriers to entry into the labor market. The proposed mechanism suggests that individuals substitute delivery jobs for criminal activities. This assumption is consistent with the previous results. We observe a sharp increase in the

Figure 10: Food Delivery Platform Entry and Drug Crime in Regional Police Jurisdictions



Notes: Event-study estimates using *the logarithm of drug crime rates* as the dependent variable. The sample is restricted to regional police jurisdictions only. Estimators used are the followings: TWFE-OLS, Callaway & Sant'Anna (2021) and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. Standard errors clustered at the jurisdiction level.

number of riders in jurisdictions associated with platform entry. We also observe a decrease in unemployment rates, inactivity and social benefits.

This section investigates the motivations behind individuals' involvement in drug-related criminal activity, which the literature considers a low-skill criminal activity. The underlying assumption is that the wage premium of dealing drugs hardly compensates for the risks involved. If this mechanism holds true, then a portion of the decrease in drug crime can be attributed to a reduction in drug trafficking activities carried out for financial gain. Thus, we now focus on decomposing the effect between different types of drug-related crimes. Specifically, we estimate the impact of platform entry on drug usage and drug dealing. Based on our mechanism, we anticipate that new delivery job opportunities will have a greater impact on drug dealing than on drug usage.

As explained in Data section 3.3, the gradual introduction of a new crime recording software between 2012 and 2015 impedes the use of the urban police disaggregated data. Therefore, we concentrate our analysis only on regional police jurisdictions. Out of the 301 regional police jurisdictions in our sample, 19 reported no drug dealing crimes in a year. We exclude them from the following estimates.[43]

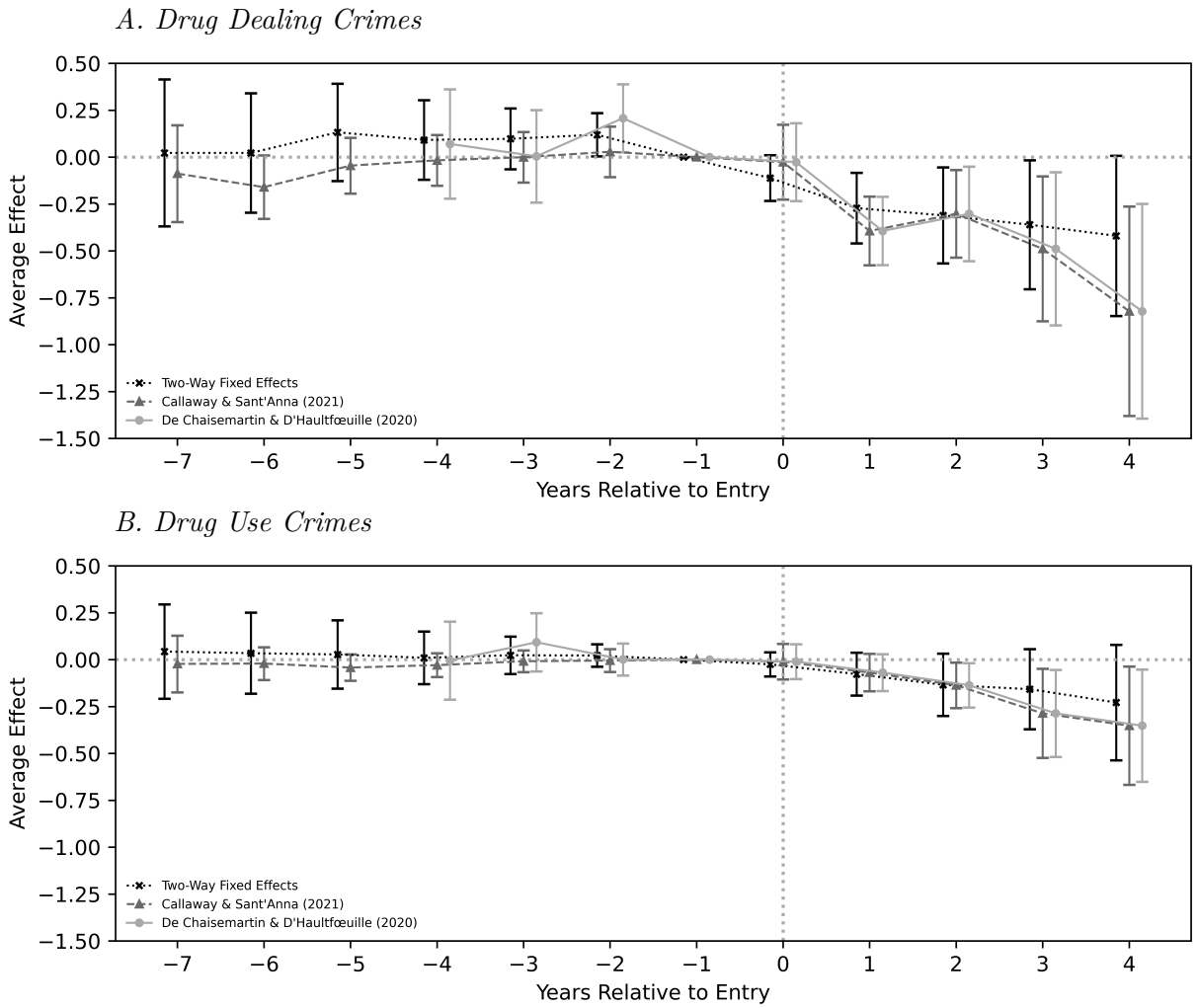
Figure 11 presents event-study plots of platform entry on drug dealing crime rates (Panel A) and drug use crime rates (Panel B) in regional police jurisdictions. Estimates

[43] All previous results remain the same when we exclude these jurisdictions from the estimates.

of pre-treatment periods indicate that parallel trends and no anticipation assumptions are verified for both types of drug crimes. As expected, the effect of platform entry appears to be relatively larger for drug dealing crimes than for drug use crimes. Accounting for treatment heterogeneity, post-treatment estimates indicate that a food delivery platform entry leads to a 56% reduction in the drug dealing crime rate after 4 years, compared to a 29.9% reduction in the drug use crime rate. The decrease in drug offenses suggests that individuals are substituting delivery jobs for drug offenses due to financial and risk reasons. The decrease in drug use may reflect a decrease in demand following a decrease in supply, as we observe a decrease in drug dealing crimes following platform entry. Alternatively, it may simply reflect a reduction in the number of arrests for trafficking offenses that have been reclassified as drug use because dealers have an incentive to carry and sell smaller quantities (see section 2).

Previous estimates have relied on platform entry to assess the impact of delivery jobs on drug crime. Although the staggered difference-in-differences method offers a clear identification strategy, it does not provide much insight to evaluate the intensive margin of platform entry on crime. However, we expect that jurisdictions with a higher number of riders will experience a greater reduction in drug crime. To measure this intensity, we estimate Appendix equation 2 using the number of riders per capita. Results are presented in Appendix G. Overall, they indicate a negative and statistically significant effect of riders per capita on the drug crime rate. Similarly to staggered difference-in-difference estimates, increases in the number of riders have a relatively greater effect on drug trafficking crimes than on drug use crimes. The results are consistent with drug crimes being substituted by delivery jobs for financial and risk reasons.

Figure 11: Food Delivery Platform Entry and Drug Dealing and Usage Crime Rates in Regional Police Jurisdictions



Notes: Event-study estimates as defined in equation 1 using *the logarithm of the drug dealing crime rate and drug usage crime rate* as the dependent variable instead of the total drug crime rate. The estimates only include regional police jurisdictions. In addition, jurisdictions recording 0 dealing drug crime for a year are excluded from the sample. Methods used are: TWFE-OLS, Callaway & Sant'Anna (2021) and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. Standard errors clustered at the jurisdiction level.

6 Conclusion

While digital platforms have sparked an extensive debate about potential negative spillovers, particularly in terms of job quality, the gig economy offers work flexibility and increases employment rates for workers who cannot find work arrangements offline (Huang *et al.*, 2020a). The present paper provides empirical evidences on this tension. To our knowledge, this is the first contribution in the empirical literature that provide evidences on the impact of gig economy on employment and crime rate. In this paper, we leverage the staggered introduction of online food delivery platforms in France to examine their impact

on employment and crime rate. Online food delivery platforms offer several benefits to employers relative to other online labor markets. First, they do not require any specific skills, unlike ride-sharing platforms, where a driver's license is mandatory. Second, they have very low entry costs, as riders only need a basic and cheap bike, while ride-sharing platforms require a car. Third, the administrative process to register is simple and free, and even riders with minor criminal records are not prevented from working for the platform, giving them the opportunity to enter the formal job market. Fourth, the entry of digital delivery platform in a city may take away labor from people who would have otherwise chosen to be involved in low-skill criminal activities.

We show that the entry of these platforms reduce crime by providing job opportunities to low-skilled and young individuals.

Our staggered difference-in-differences estimates show that the entry of these platforms not only increases the number of riders, but also reduces crime. In addition, we examine the mechanisms driving these effects, such as a reduction in inactivity and a reduced demand for social welfare.

Our results carry important policy implications. While the gig economy is often criticized for precarious working conditions and limited protections, platforms provide legal employment opportunities for low-skilled workers who face discrimination in the traditional job market to secure legal employment. Policymakers should consider strategies to expand access to stable, low-skilled employment for marginalized groups as an alternative to informal or illegal work. The findings of this study can help policymakers and platforms better understand the factors driving individuals to supply labor to these platforms.

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Appendix

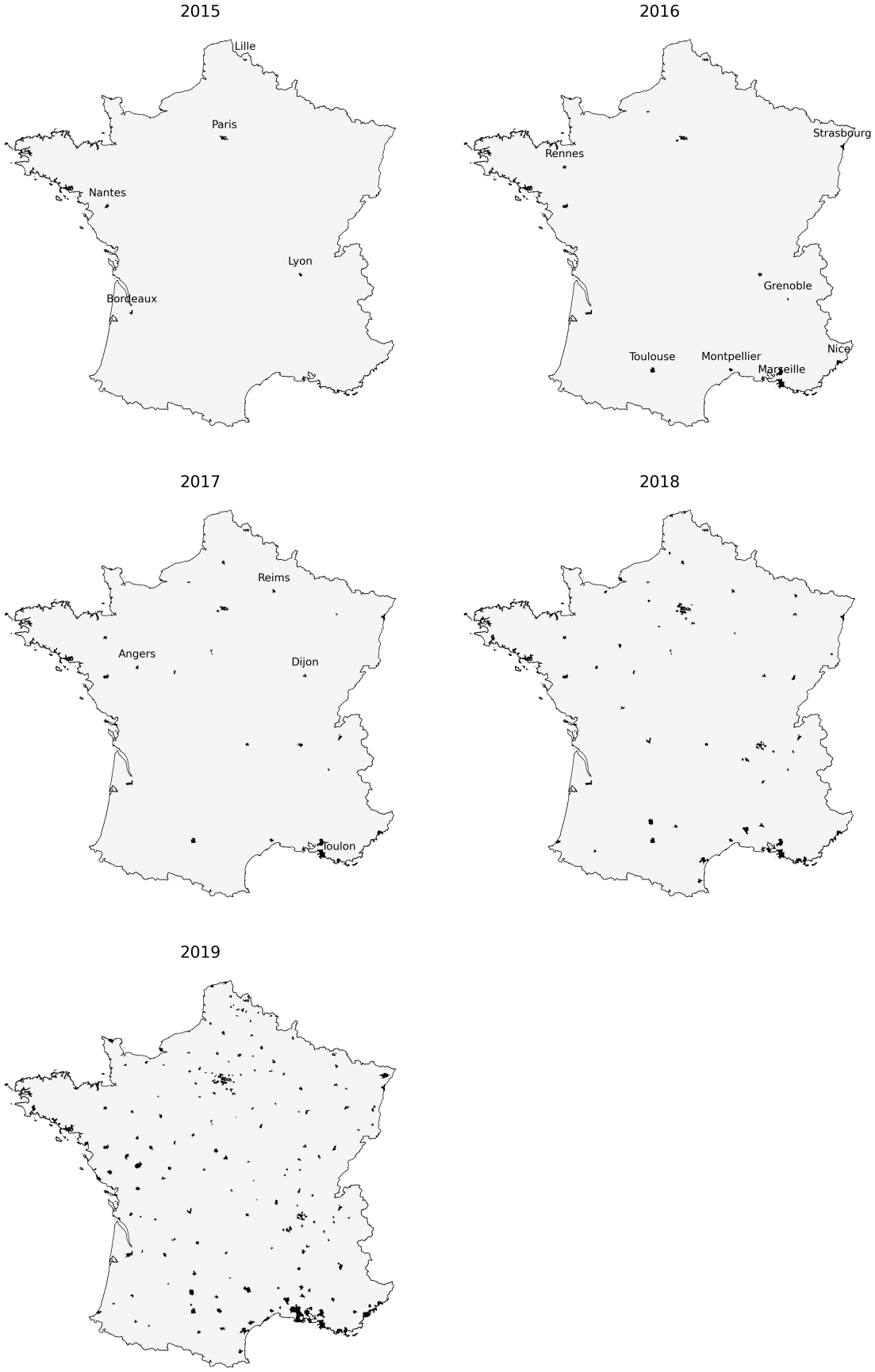
A Uber Eats and Deliveroo Rollout in France

Data on Deliveroo and Uber Eats entry dates were collected by compiling information from national and regional media outlets. Then, we cross-checked and complemented our dataset based on data provided by the *Collectif 'Data + Local'*.[44] To make sure that our enriched dataset covers all main reference markets and their surrounding areas, we use comprehensive information from Uber Eats. First, we employed the Wayback Machine website to retrospectively gather all entry dates from the company's website.[45] Second, Uber shared information with us about its 'reference markets', which had an average population of approximately 50,000 inhabitants in 2019. Although we could not access equivalent information for Deliveroo, we find reassurance in three key observations: First, we successfully and independently retrieved the entry dates for all of Uber Eats' reference markets dating back to 2015. Second, there is a strong correlation between entry dates and locations for both Uber Eats and Deliveroo. Finally, the increase in the number of registered riders in a city coincides with the first entry date of a platform. As of 2019, Uber Eats and Deliveroo are available in 2,114 cities, covering most of the country and representing 57% of the French population (see Appendix Figure 12).

[44] This 'Collectif' is a consortium of journalists and editorial teams covering all the main local medias in France. See Collectif 'Data + Local'.

[45] Unfortunately, Deliveroo does not display the entry dates on its website.

Figure 12: Uber and Deliveroo Rollout in French Cities, 2015-2019

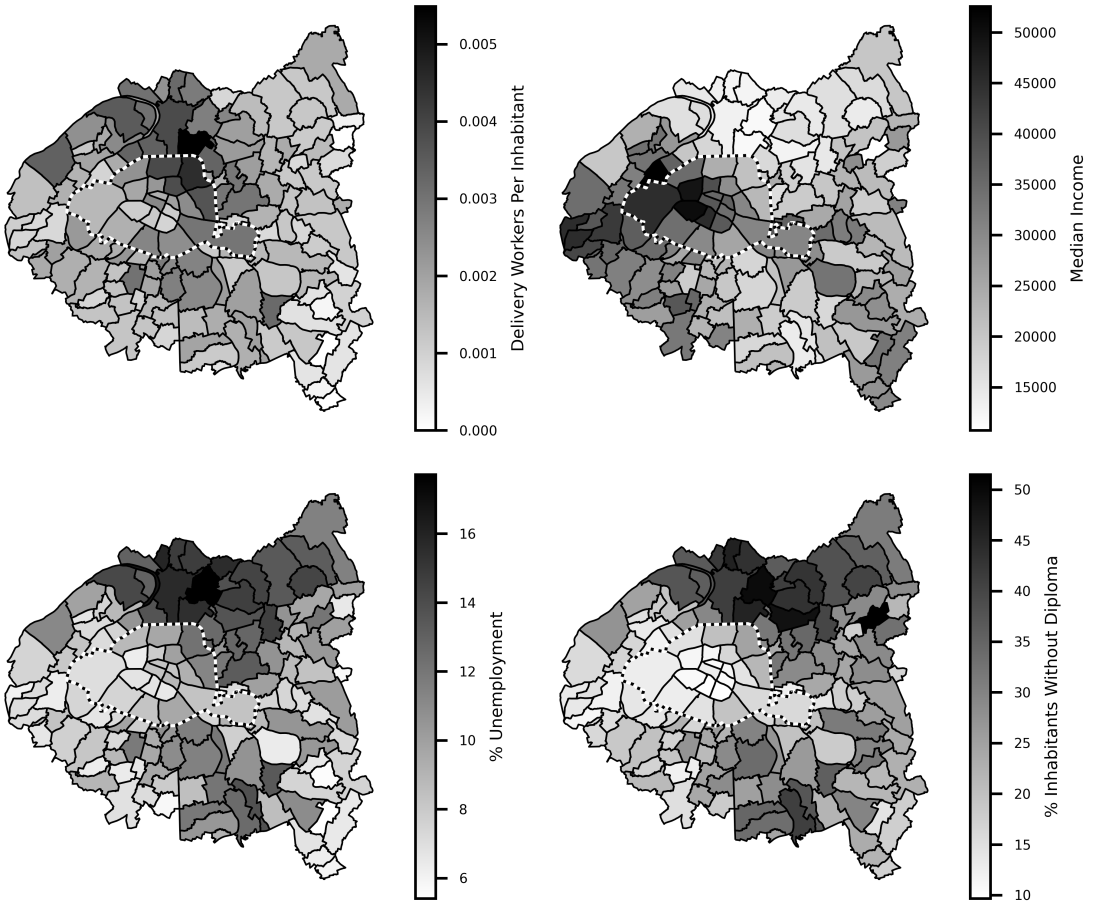


Note: Entry dates of Uber Eats and Deliveroo in French municipalities from 2015 to 2019.

B Riders

B.1 Riders and Demographics

Figure 13: Riders and Demographics in Paris and the Suburbs in 2019



B.2 Rider Demographics

The names and gender of the riders are available in the INSEE database on self-employed entities (see Section 3.2). Using the available data, we have created the three tables below to present the demographic characteristics of the drivers. Only 20% of the riders do not disclose their names.

Table 3 presents the share of males and females creating a company linked to delivering services in a given year.

The analysis of the names of the riders allows us to infer age groups and ethnicity. Table 4 presents the descriptive statistics of the riders' ages. To determine age groups, we combined our data with the registry of first names given at birth in France between

Table 3: Rider's Gender

	2012	2013	2014	2015	2016	2017	2018	2019
Female (%)	.05	.04	.04	.04	.03	.03	.03	.04
Male (%)	.95	.96	.96	.96	.97	.97	.97	.96
Non Missing Obs.	2145	2492	3018	6925	20204	29071	59310	77845
Unknown (%)	.33	.33	.29	.20	.14	.31	.36	.38
Observations	3207	3704	4,239	8,680	23,417	42,172	90,663	114,052

1900 and 2019. For each name and year, we calculated the frequency of the name over the past 80 years relative to its frequency within a defined age group. We then assigned an age group to each name per year by selecting the most likely age group based on this analysis.

Table 4: Estimated Rider's Ages

		2012	2013	2014	2015	2016	2017	2018	2019
Age Class (%)	15-19	.04	.05	.06	.09	.10	.11	.11	.12
	20-24	.06	.06	.06	.08	.07	.06	.05	.05
	25-29	.11	.12	.09	.10	.11	.11	.10	.09
	30-34	.20	.21	.24	.18	.15	.15	.17	.09
	35-39	.08	.10	.07	.05	.11	.17	.19	.27
	40-44	.11	.13	.12	.13	.09	.07	.08	.07
	45-49	.11	.10	.09	.08	.08	.08	.09	.09
	50-54	.06	.05	.05	.05	.04	.08	.06	.07
	55-59	.04	.01	.02	.02	.03	.02	.03	.03
	60-64	.06	.04	.03	.02	.02	.01	.01	.01
	65-69	.01	.05	.06	.07	.05	.05	.02	.02
	70-74	.01	.00	.00	.00	.00	.02	.07	.07
	75plus	.11	.08	.11	.14	.15	.07	.02	.01
Non missing Obs.		4,207	4,382	5,333	11,495	32,010	41,821	85,021	110,030
Missing (%)		.63	.67	.63	.57	.52	.70	.72	.72
Observations		11,291	13,006	14,321	26,979	66,156	138,155	307,873	386,852

Lastly, we can infer the ethnicity of riders from their first and last names using an algorithm developed by Hafner *et al.* (2023), which is freely available on their website. Table 5 presents the descriptive statistics of the ethnicity of riders based on the administrative data registered.

Table 5: Estimated Rider's Ethnicity (%)

	2012	2013	2014	2015	2016	2017	2018	2019
African	.05	.05	.04	.05	.06	.06	.05	.06
Asian	.02	.01	.02	.02	.02	.02	.02	.02
European	.42	.38	.40	.48	.44	.34	.30	.26
Hispanic	.11	.10	.10	.14	.12	.11	.10	.10
Arabic	.40	.46	.43	.31	.36	.48	.52	.57
Non Missing Obs.	1,874	2,147	3,602	12,786	43,402	65,979	143,697	197,611
Missing (%)	.17	.17	.14	.09	.07	.11	.10	.08
Observations	2,266	2,573	4,203	14,109	46,716	73761	160,491	215,428

C Police Jurisdictions and Crime Appendix

C.1 Crime Classification

The "État 4001" classification has been used by both urban and regional police forces since 1972. However, following the introduction of procedure records software, we register some breaks in the data. First, distinct software applications were implemented between urban police (LRPPN[46]) and regional police (LRPGN[47]). Second, these software packages are based on the "International Classification of Offences for Statistical Purpose" - NATINF in French - leading to a subsequent conversion to "Etat 4001" indexes. The transition from NATINF to "Etat 4001" is semi-automatic for urban police but completely manual for regional police. Third, software introduction started in 2012 to October 2014 for urban police, and in 2012 for regional police. However, the regional police software was initially based on the "État 4001" classification and evolved between 2015 and 2016 to leave more space for NATINF classification.

C.2 Data Management Procedures

In this section, we describe the data management procedures employed to exploit the raw dataset "État 4001," which comprises yearly crime data by police jurisdiction since 2012 (see Section 3.3). This dataset presents three main challenges.

First, certain urban police jurisdictions possess inter-regional or national responsibilities, including central and regional directions, regional security, river and public transport,

[46] logiciel de rédaction des procédures de la police nationale
[47] logiciel de rédaction des procédures de la gendarmerie nationale

Stade de France special force, night delinquency, road accidents, border and customs, illegal immigration, financial and tax crimes, cyber crimes, trafficking of cultural goods, human trafficking, organized crime, gambling regulation, task forces, terrorism, and supervision of other police forces. These jurisdictions are excluded from the dataset as crimes cannot be localized to a specific area, which is essential for our identification strategy. Conversely, regional police have well-defined geographical jurisdictions for all areas.

Second, some jurisdictions have either merged or split between 2012 and 2021.To maintain a consistent panel structure for our staggered DiD estimates, we use the most aggregated level of jurisdictions throughout the entire sample period. This ensures that all jurisdictions are consistently observed each year. In addition, we classify jurisdictions as urban or regional based on the nomenclature used in 2022.

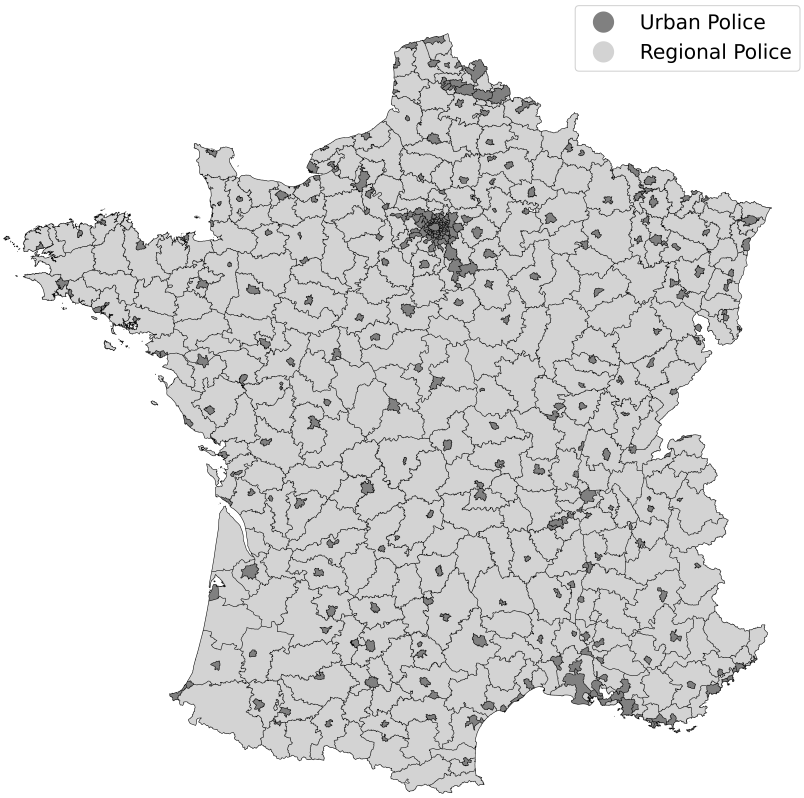
Finally, to match cities to police jurisdictions, we use the French database on territorial competencies of police forces, which provides the geographic delineation of police jurisdictions as of 2022.[48] We assume that these delineations have remained constant throughout the sample period.[49]

C.3 Figures

[48] See https://www.data.gouv.fr/fr/datasets/5489cda0c751df35a24120e7/.

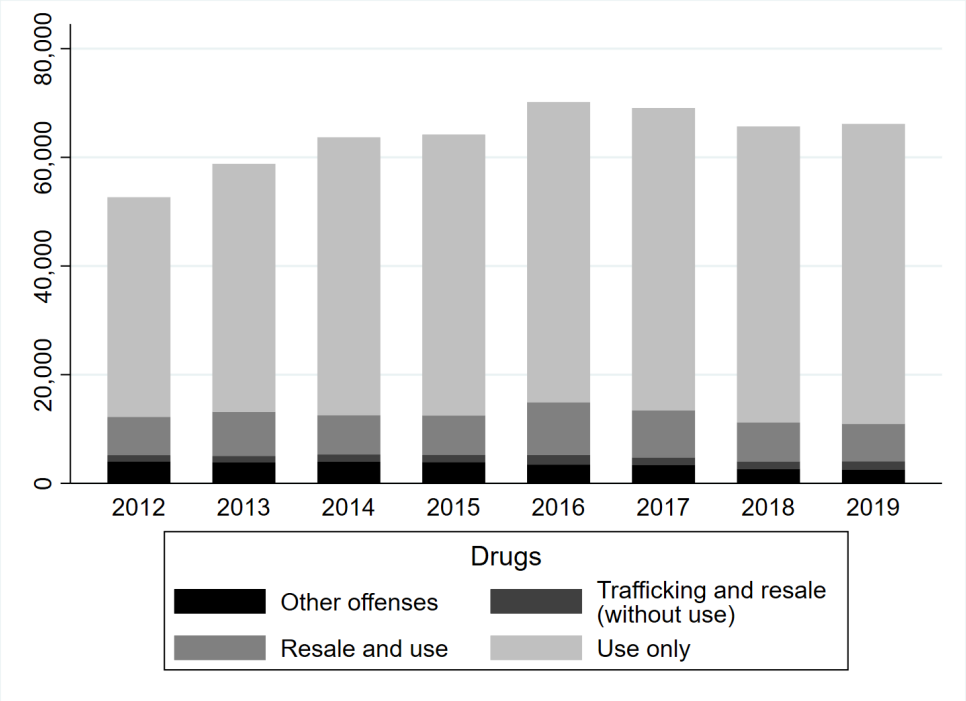
[49] This assumption is reasonable because potential mergers involve only very small towns.

Figure 14: Urban and Regional Police Jurisdictions



Note: The figure shows urban police enforcement areas in dark grey and regional police enforcement areas in light grey.

Figure 15: Number of Drug-Related Crime Registered by Categories in Rural Areas



Note: Total number of drug-related crimes registered by regional police and the breakdown by specific types of crimes.

Figure 16: Street Drug Prices



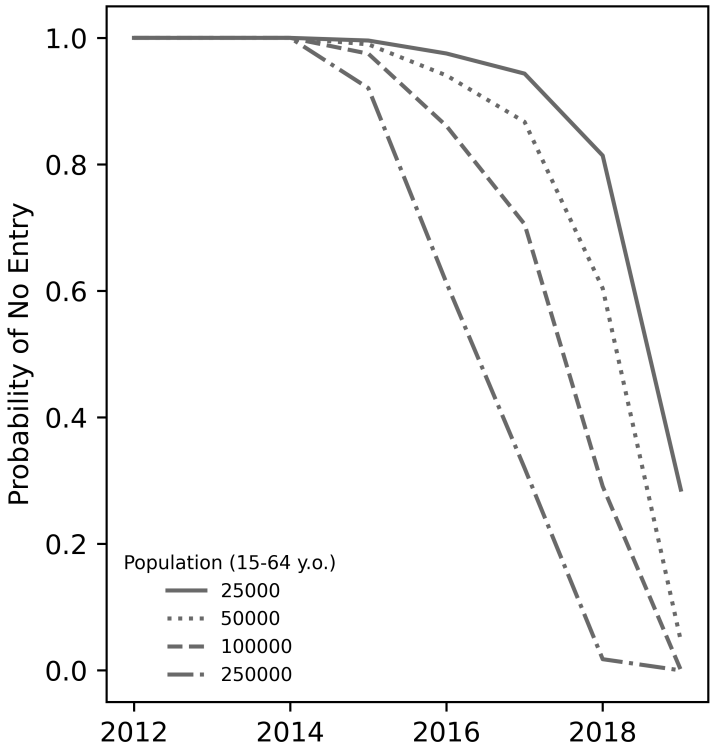
D Geographical Levels

Figure 17: Geographical Levels in Ile-De-France



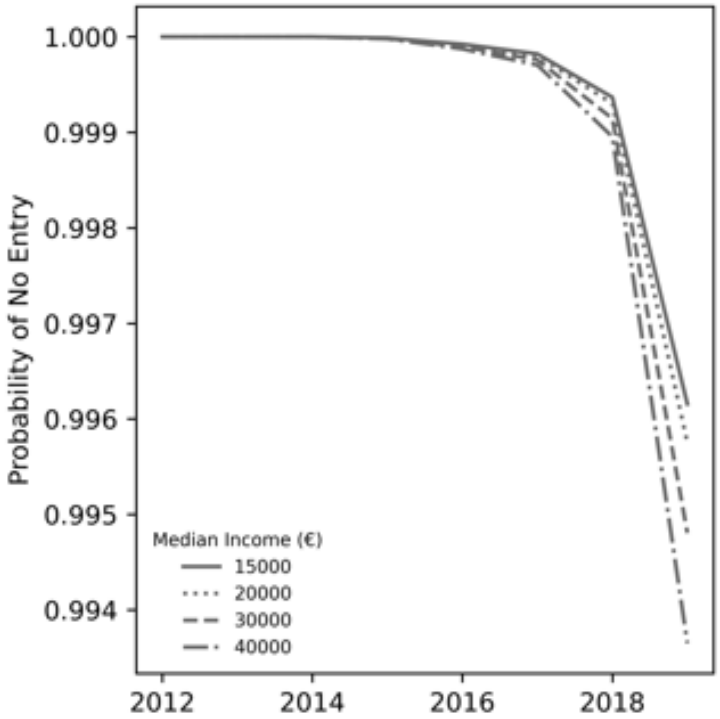
E Survival Figures

Figure 18: Survival Curves of Uber Eats Entry by City Population Size



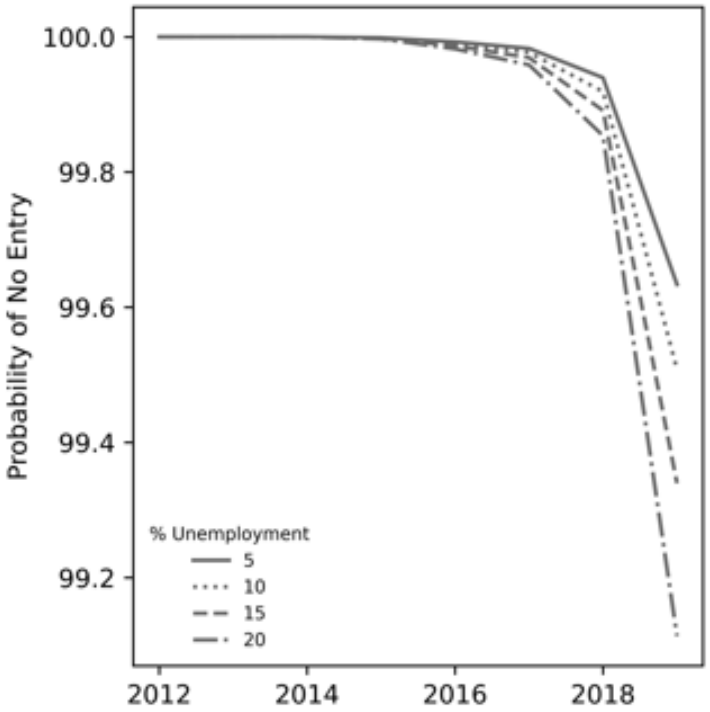
Note: The figure presents survival curves that depict the predicted likelihood of platform entry at different population size levels.

Figure 19: Survival Curves of Uber Eats Entry by City Median Income



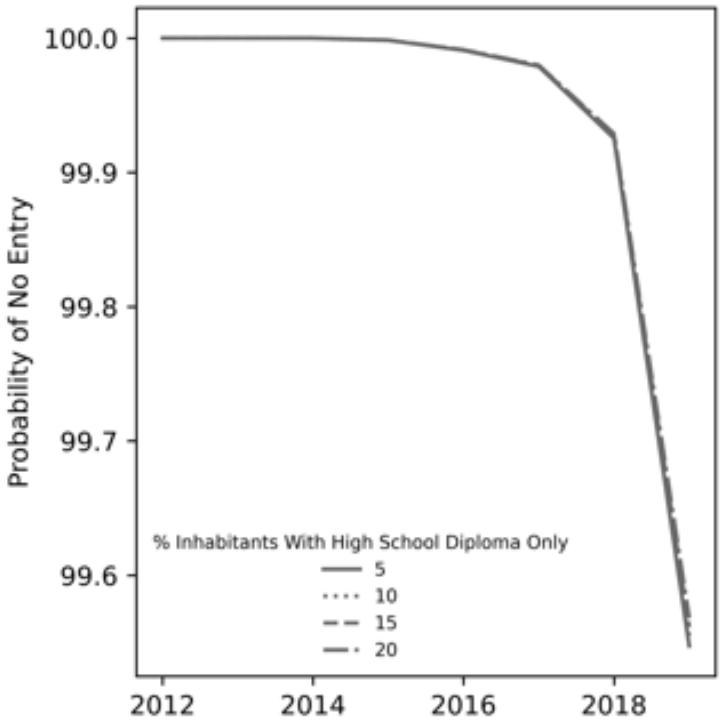
Note: The figure presents survival curves that depict the predicted likelihood of platform entry at different median income levels.

Figure 20: Survival Curves of Uber Eats Entry by City Unemployment Rate



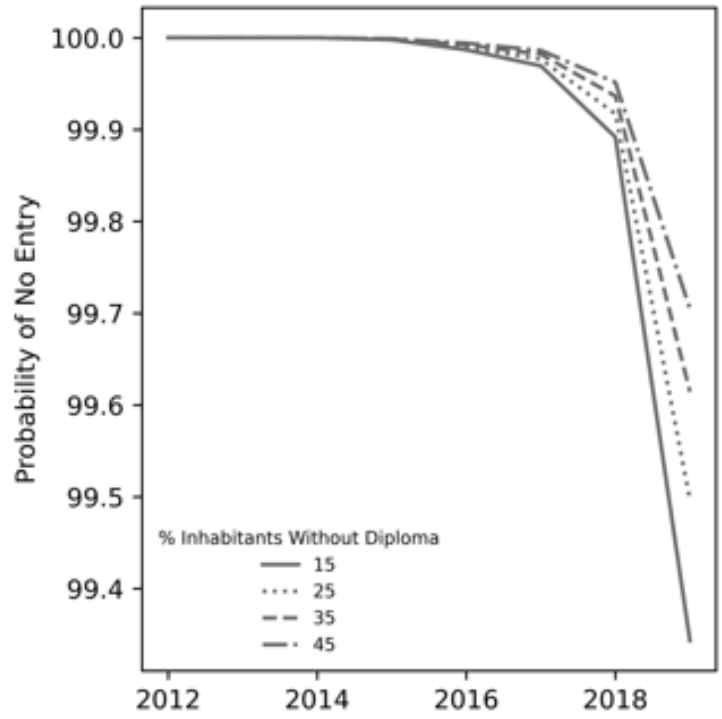
Note: The figure presents survival curves that depict the predicted likelihood of platform entry at different unemployment rates.

Figure 21: Survival Curves of Uber Eats Entry by City High-School Diploma Rate



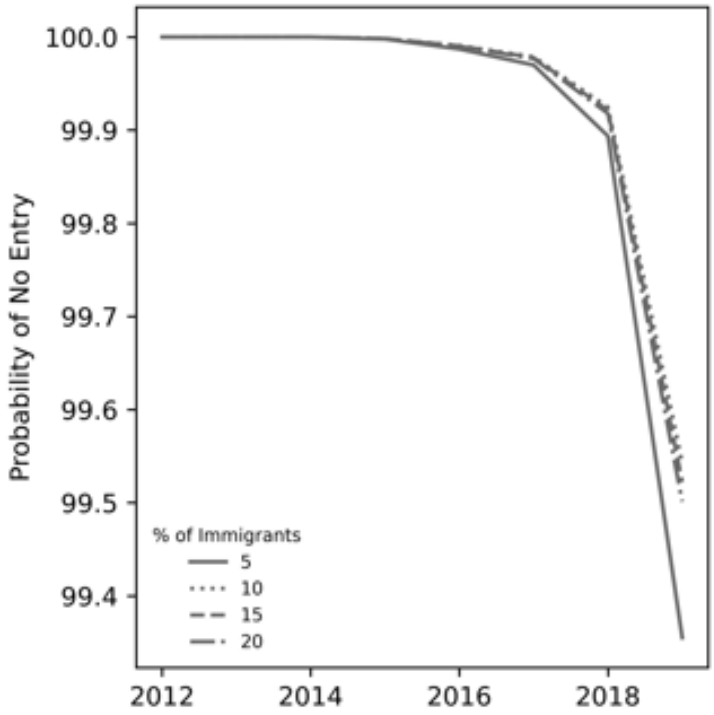
Note: The figure presents survival curves that depict the predicted likelihood of platform entry at different rates of high-school diploma.

Figure 22: Survival Curves of Uber Eats Entry by City No Diploma Rate



Note: The figure presents survival curves that depict the predicted likelihood of platform entry at different rates for individuals without a diploma.

Figure 23: Survival Curves of Uber Eats Entry by City Immigration Rate



Note: The figure presents survival curves that depict the predicted likelihood of platform entry at different immigration rates.

F Impact on Social Benefits

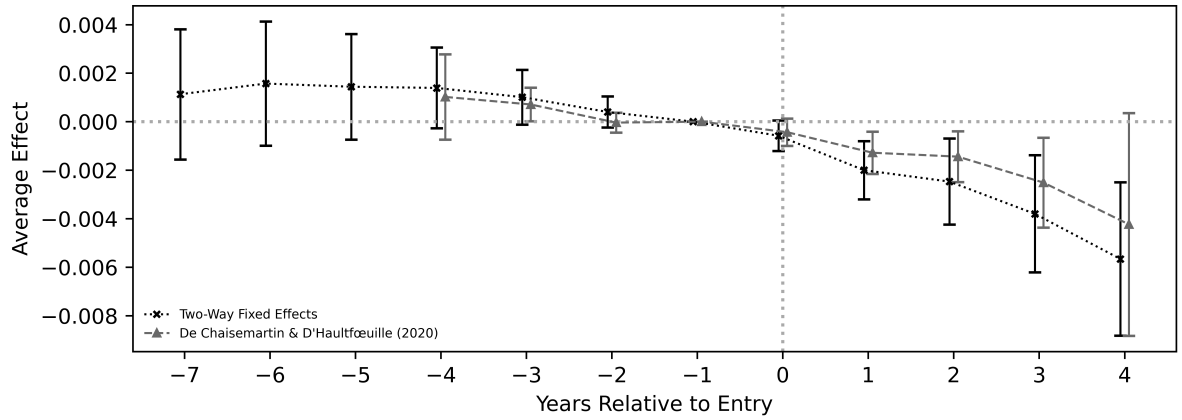
Figure 24 presents event-study plots of platform entry on the share of social benefits in household disposable income. Social benefits are public transfers, in cash or in kind, to individuals or families for protection against various risks. Social benefits include transfers for 6 major risk categories: old age and survival, health, maternity-family, job loss, housing difficulties, and poverty and social exclusion.[50]

Panel A shows the results for regional jurisdictions using the 15km buffer, while Panel B shows the results for urban jurisdictions. For context, the average share of social benefits for statutory minimum across jurisdictions, the year before treatment, is approximately 5.2% in regional jurisdictions and 7.2% in urban jurisdictions. For both regional and urban jurisdictions, pre-treatment estimates are consistent with the parallel trends and no anticipation assumptions. Post-treatment estimates indicate a decrease in the the share of social benefits in household1 disposable in both types of jurisdictions. After 4 years, post-treatment estimates indicate that platform entry decreases the share of social benefits by 0.42 p.p. in regional jurisdictions and by 0.83 p.p. in urban jurisdictions. These findings suggest that food delivery jobs have substituted for financial aid by increasing income. In other words, the increase in revenue induced by delivery jobs reduces amounts of aid received in addition to the number of individuals eligible to these aids.

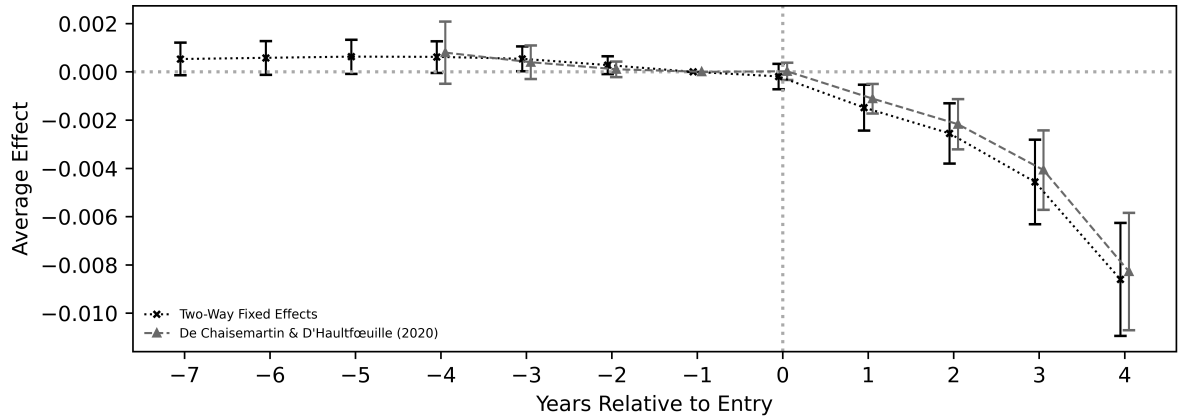
[50] See https://www.insee.fr/en/metadonnees/definition/c1562 for further details.

Figure 24: Share of Social Benefits in Police Jurisdictions

A. Regional Jurisdictions



B. Urban Jurisdictions



Notes: Event-study estimates as defined in equation 1 using the share of social benefits over household disposable income as the dependent variable instead of the total drug crime rate. Methods used are: TWFE-OLS and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. The population from 15 to 64 years old is included as a control. Standard errors clustered at the jurisdiction level.

G The Intensive Margin

G.1 The Instrumental Variable Approach

The DiD method captures the *extensive margin*, i.e., the average impact of the platform entry on crime. The *intensive margin* measures the impact based on the intensity of the number of riders. Our second identification strategy allows us to estimate this intensive margin. To address the potential endogeneity of the number of riders, we use an instrumental variable (IV) approach. The dummy variables indicating the time since platform entry are potential candidates for instrumental variables. First, the relevance of these

instrumental variables is related to the duration required for food delivery platforms to expand their operations following entry. Second, the staggered Difference-in-Differences (DiD) results suggest that the platform's entry decision is exogenous to drug crimes, conditional on area characteristics. Consequently, the platform's entry date satisfies the exclusion restriction condition necessary for a valid instrument.

The set of instruments also includes post-treatment dummy variables indicating the number of years since platform entry. The running time of the platform in a jurisdiction may affect some unobserved factors influencing drug crimes committed by riders. For instance, one might hypothesize that after several years of working for food delivery platforms, some riders might engage in crime due to poor working conditions, either by consuming drugs or by selling drugs as a supplementary income. However, this is an indirect effect of time on drug crimes, as the existence of this mechanism is conditional on the rider's participation in the platform. Since the set of instruments includes all treatment variables for all years prior to the emergence of such a mechanism, the exclusion restriction is satisfied. .More specifically, we estimate the following model:

$$\log\left(\frac{\text{Drug Crimes}}{\text{Population}}\right)_{zt} = \alpha_z + \lambda_t + \beta \log\left(\frac{\text{Riders}}{\text{Population}}\right)^{d}_{zt} + \gamma X_{zt} + \epsilon_{zt} \tag{2}$$

where $\left(\frac{\text{Riders}}{\text{Population}}\right)^{d}_{zt}$ is the rider per capita within a maximum distance of d kilometers from area z in year t. We take into account the spillover effects of riders when $d > 0$. We denote by X_{zt} the observable socio-demographic characteristics of the area z in year t. Finally, ϵ_{zt} is the error term that is assumed to be i.i.d.

The IV approach offers significant advantages. First, it extends the analysis to include all delivery platforms with self-employed workers in France. Second, by using the rider per capita, we estimate the marginal impact of an additional delivery worker on the drug crime rate.

G.2 Number of Riders and Drug Crimes

Table 6 shows the impact of riders per capita on the drug crime rate. The estimates correspond to β and γ in equation 2, with $d = 0$ meaning that results do not account for the spillover effects of riders in neighboring cities. Columns (1) and (3) present the estimates without instrumenting for riders per capita. Although OLS results indicate

Table 6: Riders per Capita and Drug Crime Rate

	Dependent variable: Drug Crime Rate			
	Urban Police		Regional Police	
	OLS	GMM	OLS	GMM
	(1)	(2)	(3)	(4)
log(Riders per Capita)	-0.0475***	-0.0755***	-0.0352	-0.1321**
	(0.015)	(0.020)	(0.024)	(0.053)
Unemployment Rate	5.3327*	4.7908*	6.2480	5.0203
	(2.927)	(2.830)	(5.589)	(5.601)
Immigrant Rate	0.1564	1.1644	6.2057	10.3279
	(1.770)	(1.830)	(5.818)	(6.340)
Median Income	-0.0006	-0.0004	-0.0026	-0.0022
	(0.002)	(0.002)	(0.002)	(0.002)
log(Policemen per Capita)	0.0085	0.0048	0.9492***	0.8216***
	(0.021)	(0.020)	(0.198)	(0.203)
Year FE	Yes	Yes	Yes	Yes
Jurisdiction FE	Yes	Yes	Yes	Yes
Weak Identification KP Stat		41.492		15.607
Underidentification KP Stat.		125.785		89.204
Hansen J Stat.		7.314		4.540
Observations	2,720	2,720	2,728	2,728

The dependent variable is the logarithm of the drug crime rate. The sample used in columns (1) and (2) includes urban police jurisdictions, while the sample used in columns (3) and (4) includes regional police jurisdictions. The instruments used in GMM estimations are 11 dummy variables indicating the relative time since the first platform entry. The first stage is similar to an event-study TWFE OLS estimation of platform entries on riders per capita. Standard errors clustered at the jurisdiction level. Significance: * <0.1, ** <0.05, *** <0.01

that an increase in riders per capita in urban police jurisdictions significantly decreases the drug crime rate, the effect is negative but insignificant in regional police jurisdictions. In columns (2) and (4), we instrument riders per capita with dummy variables indicating the relative time since the first entry of a food delivery platform in a jurisdiction. More precisely, we assume that urban police jurisdictions are treated when a platform enters the jurisdiction, while regional police jurisdictions are treated when a platform enters the jurisdiction or a city within 15 kilometers of the jurisdiction boundary. These assumptions are backed up by Figures 4 and 5, which show a sharp increase in riders per capita at the time of entry and motivate our first stage. The IV results indicate a negative and

significant effect of riders per capita on the drug crime rate for both urban and regional police jurisdictions. A 1% increase in riders per capita decreases the drug crime rate in urban police jurisdictions by 0.076% (column 2). While first-stage and overidentification tests[51] suggest that instruments are valid and relevant for urban police jurisdictions, the F-stat on excluded instruments (=15.6) for regional police jurisdictions suggests that instrumental variables only weakly identify riders per capita. Therefore, the coefficient for regional police jurisdictions should be viewed with caution and advocates to allow for spillover effects as shown in Table 8.

Table 7: Buffer Estimations of Riders on Drug Crime Rate in Urban Police Jurisdictions

	Dependent variable: Drug Crime Rate			
	(1)	(2)	(3)	(4)
log(Riders per Capita)	-0.0755***			
	(0.020)			
log(Riders per Capita at 5km)		-0.0904***		
		(0.024)		
log(Riders per Capita at 10km)			-0.0978***	
			(0.027)	
log(Riders per Capita at 15km)				-0.1035***
				(0.029)
Unemployment Rate	4.7908*	4.7062	4.8466*	4.5464
	(2.830)	(2.871)	(2.893)	(2.926)
Immigrant Rate	1.1644	1.2891	1.2779	1.3898
	(1.830)	(1.878)	(1.879)	(1.899)
Median Income	-0.0004	-0.0001	-0.0000	0.0001
	(0.002)	(0.002)	(0.002)	(0.002)
log(Policemen per Capita)	0.0048	0.0018	0.0011	0.0008
	(0.020)	(0.021)	(0.021)	(0.021)
Year FE	Yes	Yes	Yes	Yes
Urban Police FE	Yes	Yes	Yes	Yes
Weak Identification KP Stat.	41.4917	37.3885	31.6556	29.1700
Underidentification KP Stat.	125.7845	117.4290	104.4446	99.7318
Hansen J Stat.	7.3143	7.3646	7.9599	8.3633
Observations	2,720	2,720	2,720	2,720

The dependent variable is the logarithm of the drug crime rate. Results are computed using GMM. The sample includes urban police jurisdictions only. The instruments used are 11 dummy variables indicating the relative time since the first platform entry. The first stage is similar to an event-study TWFE OLS estimation of platform entries on the delivery worker rate. Standard errors clustered at the "Police" jurisdiction level. Significance: * <0.1, ** <0.05, *** <0.01

[51] The null hypothesis that all instruments are valid is not rejected at a significance of 10%.

Table 7 presents the robustness results of IV estimates with buffers (i.e., $d \geqslant 0$ in equation 2) on riders per capita in urban police jurisdictions. We use the same instruments as in Table 6 and report its column (2) as our benchmark column (1). The first-stage and overidentification tests suggest that instruments are valid and relevant. The results from columns (1) to (4) indicate an increase in the impact of riders per capita on the drug crime rate as we allow for farther-reaching spillover effects. This suggests that the increasing delivery job opportunities in neighboring cities can reduce the drug crime rate in the urban police jurisdiction. Specifically, a 1% increase in riders per capita within a 15-kilometer distance results in a 0.103% decrease in the drug crime rate of the urban police jurisdiction.

Table 8 presents the same buffer strategy as Table 7 for regional police jurisdictions. We use also the same instruments as in Table 6 and report its column (4) as our benchmark column (1). As shown previously, the F-stat on excluded instruments in column (1) indicates that instrumental variables weakly identify riders per capita when we do not allow for spillover effects. However, columns (2) to (4) demonstrate that instruments are more robust when accounting for spillover effects and provide more accurate estimates. The estimates indicate a negative and significant effect of riders per capita on the drug crime rate. A 1% increase in riders per capita within a 5-kilometer distance of the regional police jurisdiction decreases its drug crime rate by 0.107%. This effect is slightly attenuated as the buffer distance increases, suggesting the incorporation of more irrelevant cities as the distance to the regional police increases.

Table 9 presents the IV results with buffers on riders per capita with the drug *dealing* crime rate as the dependent variable, in regional police jurisdictions. The coefficients correspond to β and γ in equation 2, but with the log of the drug resale crime rate on the left side of the equation. The instruments are similar to those used previously. Column (1) shows the results without buffers on riders per capita. Again, the instruments show weak identification of riders per capita. Moreover, the null hypothesis that all instruments are valid is rejected at the 10% significance level. Consequently, the results without buffers should be treated with great caution. However, first stage and overidentification tests with buffers in columns (2) to (4) suggest that the instruments are valid and relevant.[52] The results indicate a negative and statistically significant effect of riders per capita on

[52]The null hypothesis that all instruments are valid is not rejected at a significance of 10%.

Table 8: Buffer Estimations of Riders on Drug Crime Rate in Regional Police Jurisdictions

	Dependent variable: Drug Crime Rate			
	(1)	(2)	(3)	(4)
log(Riders per Capita)	-0.1321**			
	(0.053)			
log(Riders per Capita at 5km)		-0.0746**		
		(0.031)		
log(Riders per Capita at 10km)			-0.0622**	
			(0.026)	
log(Riders per Capita at 15km)				-0.0566**
				(0.023)
Unemployment Rate	5.0203	5.8154	5.5180	5.1638
	(5.601)	(5.587)	(5.549)	(5.550)
Immigrant Rate	10.3279	7.6926	7.4419	7.1694
	(6.340)	(5.955)	(5.922)	(5.884)
Median Income	-0.0022	-0.0022	-0.0021	-0.0024
	(0.002)	(0.002)	(0.002)	(0.002)
log(Policemen per Capita)	0.8216***	0.8196***	0.8278***	0.8510***
	(0.203)	(0.201)	(0.199)	(0.195)
Year FE	Yes	Yes	Yes	Yes
Reagional jurisdiction FE	Yes	Yes	Yes	Yes
Weak Identification KP Stat.	15.6068	25.2776	51.1477	92.8017
Underidentification KP Stat.	89.2038	127.6956	166.6638	187.4553
Hansen J Stat.	4.5402	5.2280	5.3225	5.2095
Observations	2,728	2,728	2,728	2,728

The dependent variable is the logarithm of the drug crime rate. Results are computed using GMM. The sample includes regional police jurisdictions only. The instruments used are 11 dummy variables indicating the relative time since the first platform entry. The first stage is similar to an event-study TWFE OLS estimation of platform entries on the delivery worker rate. Standard errors clustered at the regional jurisdiction level. Significance: * <0.1, ** <0.05, *** <0.01

the drug resale crime rate. Similarly to results inTable 8, an increase in the buffer distance attenuates the effect of riders on the drug resale crime rate. Nevertheless, all results are negative and significant. A 1% increase in riders per capita within 5 kilometers of the jurisdictional boundary reduces the drug dealing crime rate by 0.21%. The effect decreases to 0.17% at a distance of 15 kilometers.

Table 9 uses as dependent variable *Drug use crime rate*. The coefficient associated with riders per capita is again only weakly identified by the instruments without using buffers. However, the first-stage and overidentification tests, which include buffers in

Table 9: Buffer Estimations of Riders on Drug Dealing Crime Rate in Regional Police Jurisdictions

	Dependent variable: Drug Dealing Crime Rate			
	(1)	(2)	(3)	(4)
log(Riders per Capita)	-0.2474***			
	(0.083)			
log(Riders per Capita at 5km)		-0.1873***		
		(0.053)		
log(Riders per Capita at 10km)			-0.1576***	
			(0.044)	
log(Riders per Capita at 15km)				-0.1480***
				(0.040)
Unemployment Rate	15.8865*	15.3118*	14.2102	12.9601
	(8.710)	(8.859)	(8.899)	(8.921)
Immigrant Rate	10.8914	6.4016	6.2418	5.7116
	(10.981)	(10.809)	(10.789)	(10.664)
Median Income	-0.0068**	-0.0067**	-0.0065**	-0.0071***
	(0.003)	(0.003)	(0.003)	(0.003)
log(Policemen per Capita)	0.3787	0.3455	0.3599	0.4110
	(0.260)	(0.267)	(0.263)	(0.254)
Year FE	Yes	Yes	Yes	Yes
Regional Jurisdiction FE	Yes	Yes	Yes	Yes
Weak Identification KP Stat.	15.1174	23.7945	48.7427	88.6551
Underidentification KP Stat.	85.7861	121.5124	160.1933	179.7713
Hansen J Stat.	14.6736	10.4575	10.5069	10.2077
Observations	2,576	2,576	2,576	2,576

The dependent variable is the logarithm of the drug reselling crime rate. Results are computed using GMM. The sample includes regional police jurisdictions only. Additionally, jurisdictions recording 0 re-selling drug crime for a year are excluded from the sample. The instruments used are 11 dummy variables indicating the relative time since the first platform entry. The first stage is similar to an event-study TWFE OLS estimation of platform entries on the delivery worker rate. Standard errors clustered at the regional jurisdiction level. Significance: * <0.1, ** <0.05, *** <0.01

columns (2) to (4), suggest that the instruments are both valid and relevant. The results indicate a negative and statistically significant effect of riders per capita on drug use crime rates, which is again attenuated as the buffer distance increases. A 1% increase in riders per capita within 5 kilometers of the jurisdictional boundary reduces the drug use crime rate by 0.08%. The effect decreases to 0.06% at a distance of 15 kilometers.

Similarly to staggered difference-in-difference results, the increase in the number of riders impacts relatively more drug dealing crimes than drug usage crimes. The results are consistent with drug crimes being substituted by delivery jobs for financial and risk

Table 10: Buffer Estimations of Riders on Drug Use Crime Rate in Regional Police Jurisdictions

	Dependent variable: Drug Use Crime Rate			
	(1)	(2)	(3)	(4)
log(Riders per Capita)	-0.0721			
	(0.054)			
log(Riders per Capita at 5km)		-0.0439		
		(0.033)		
log(Riders per Capita at 10km)			-0.0367	
			(0.027)	
log(Riders per Capita at 15km)				-0.0340
				(0.025)
Unemployment Rate	4.9456	5.0418	4.7957	4.5371
	(6.160)	(6.211)	(6.226)	(6.236)
Immigrant Rate	4.8719	3.3283	3.2360	3.1254
	(6.992)	(6.574)	(6.559)	(6.526)
Median Income	-0.0014	-0.0014	-0.0013	-0.0015
	(0.002)	(0.002)	(0.002)	(0.002)
log(Policemen per Capita)	1.0403***	1.0502***	1.0568***	1.0708***
	(0.248)	(0.245)	(0.243)	(0.239)
Year FE	Yes	Yes	Yes	Yes
Regional Jurisdiction FE	Yes	Yes	Yes	Yes
Weak Identification KP Stat.	15.1174	23.7945	48.7427	88.6551
Underidentification KP Stat.	85.7861	121.5124	160.1933	179.7713
Hansen J Stat.	2.0916	2.1048	2.1090	2.0369
Observations	2,576	2,576	2,576	2,576

The dependent variable is the logarithm of the drug use crime rate. Results are computed using GMM. The sample includes regional police jurisdictions only. Additionally, jurisdictions recording 0 reselling drug crime for a year are excluded from the sample. The instruments used are 11 dummy variables indicating the relative time since the first platform entry. The first stage is similar to an event-study TWFE OLS estimation of platform entries on the delivery worker rate. Standard errors clustered at the regional jurisdiction level. Significance: * <0.1, ** <0.05, *** <0.01

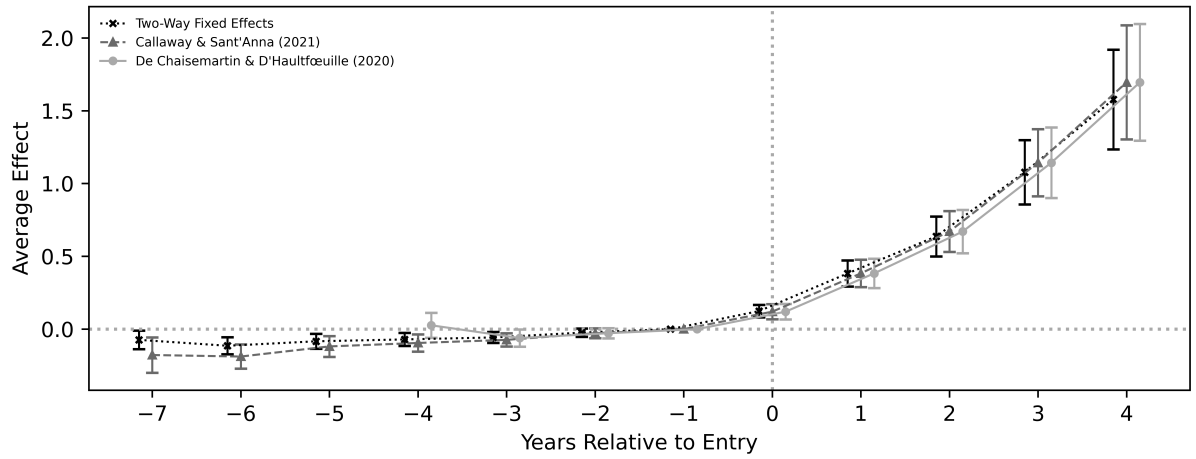
reasons. The presence of riders has a large impact on drug dealing crimes.

H Alternative Definition of Treated Units

Figure 25a shows the event-study estimates of platform entry on the number of riders for regional police jurisdictions. We revise the definition of treated units to consider a jurisdiction as treated when a platform operates within 10 kilometers of the jurisdiction's border in the city. However, under this definition, the negative pre-trend suggests that jurisdictions are considered as treated too late. This implies that using a 15-kilometer distance, as shown in Figure 5, more accurately determines the impact of platform entry on the number of riders than a 10-kilometer distance.

Figure 25: Food Delivery Platform Entry and Riders in Regional Police Jurisdictions

Treated Distance of 10 kilometers



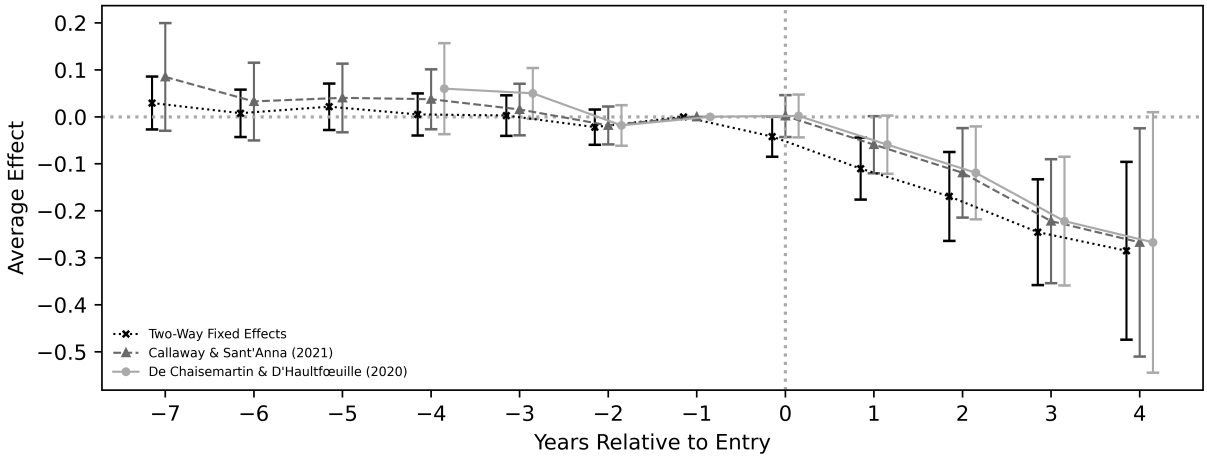
Notes: This figure displays the event-study estimates using the logarithm of riders per capita as the dependent variable. The sample is restricted to regional police jurisdictions only. Estimators used are the followings: TWFE-OLS, Callaway & Sant'Anna (2021) and De Chaisemartin & d'Haultfoeuille (2020). The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals. Standard errors clustered at the jurisdiction level.

I Crimes in Commuting Zones

Figure 26 presents the event-study plots at the commuting zone level, with estimates corresponding to β in Equation 1. The estimates appear to be consistent with the parallel trends and no-anticipation assumptions, even when the assumption of homogeneous treatment effects is relaxed. Overall, the results indicate that food delivery platforms have reduced drug-related crimes in commuting zones. In addition, the results indicate an increasing effect over time, mainly explained by the expansion of food delivery platform operations within commuting zones. After the entry, platforms need time to scale

their operations as they convince restaurants to join their application and expand their customer base. As a result, there has been a gradual increase in the number of consumers using food delivery platforms. The estimates of the food delivery platform entries resulted in a 23.5% decrease in the drug crime rate after four years. Consequently, the decrease in drug crimes observed at the police jurisdiction level is robust to spillover effects.

Figure 26: Food Delivery Platform Entry and Drug Crime in Commuting Zone



Notes: This figure presents event-study estimates derived from Equation 1 at the commuting zone level, using various estimators: TWFE-OLS, Callaway & Sant'Anna (2021) and De Chaisemartin & d'Haultfoeuille (2020). The dependent variable is the logarithm of the drug crime rate. The number of pre-treatment periods that can be estimated with De Chaisemartin & d'Haultfoeuille (2020) is limited to 3. The bars represent the 95 percent confidence intervals, with standard errors clustered at the employment zone level.