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Hugo Allouard

ESSEC Business School

Olivier Marie

Erasmus University Rotterdam, TI, IZA and CEPR

Grazia Cecere

Institut Mines Telecom

Inès Picard

Paris School of Economics, Institut des politiques publiques - CREST

José De Sousa

University of Paris Panthéon-Assas, LEMMA

Sciences Po, LIEPP

LEMMA EA 4442 - 4 rue Blaise Desgoffe 75006 Paris

Deliver Us from Crime? Gig Jobs, Labor Market Opportunities, and Offending *

Hugo Allouard[†], Grazia Cecere[‡], Jose De Sousa[§], Olivier Marie[¶], Ines Picard[‖]

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Abstract

We study how the expansion of gig job opportunities affects local labor markets and crime in France. Food delivery platforms create flexible and low-barrier jobs that attract young and minority workers from disadvantaged areas, who have limited opportunities in the traditional labor market. Using staggered difference-in-differences, we show that platform entry substantially raises labor-market participation among male migrants. We also find sizable declines in violent offenses, petty theft, vandalism, and drug crimes, consistent with increased opportunity costs of crime and reduced unstructured time among high-risk individuals. Exploiting the legal minimum age of 18 for delivery work, an age-eligibility test shows that crime reductions are concentrated among those able to take up platform jobs.

Keywords: Gig economy, crime, labor market opportunities, digital platforms

JEL classification: J68; K42; L68

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[†]Hugo Allouard: ESSEC Business School, hugo.allouard@essec.edu

[‡]Grazia Cecere: Institut Mines Telecom, grazia.cecere@imt-bs.eu

[§]José De Sousa: University of Paris Pantheon-Assas, LEMMA and Sciences Po, LIEPP, jose.de-sousa@u-paris2.fr

[¶]Olivier Marie: Erasmus University Rotterdam, TI, IZA, CESIfo and CEPR, marie@ese.eur.nl

[‖]Inès Picard: Paris School of Economics, Institut des politiques publiques – CREST, Institut Polytechnique de Paris, ines.picard@ensae.fr

1 Introduction

We study the impact of gig job availability on local labor markets and crime. Food-delivery platforms create low-barrier job opportunities in the low-skill labor market, disproportionately attracting ethnic minorities and disadvantaged youths with limited access to traditional jobs. In the United States, 7% of the adults surveyed report earning income from delivery work in 2021. However, participation is substantially higher among Hispanic, Black, young, and low-income respondents than among white, prime-age, and high-income respondents.[1] These job opportunities may prove significant because disadvantaged youth, ethnic minorities, and those with migrant background—groups facing persistent barriers to legal employment—are overrepresented in arrest and conviction records (Hjalmarsson et al., 2024; Marie and Pinotti, 2024). By expanding access to legal income for workers at the margin of the labor market, gig job availability may reduce involvement in low-skill crime.

Fifteen years ago, jobs performed by self-employed contractors on digital platforms were almost nonexistent. By 2021, there were an estimated 4.9 million gig workers in the United States (Garin et al., 2023) and up to 4.1 million in the European Union.[2] This growth stems overwhelmingly from food-delivery platforms. Food-delivery work is the archetypal task-based gig job. It provides limited unemployment benefits and job security, but offers flexibility (Einav et al., 2016; Hall and Krueger, 2018; Chen et al., 2019; Guo et al., 2024) and very low barriers to entry. Registration is free and upfront investment is minimal, with delivery (in Europe) often performed using a basic bicycle. Platforms typically do not require CVs, photographs, formal education, credentials, or language proficiency. The resulting low-screening, largely non-discriminatory hiring process makes delivery jobs accessible to the groups excluded from the labor market.

Can access to these new gig job opportunities help reduce crime? Becker (1968) frames crime as a cost-benefit calculation under uncertainty: individuals weigh the expected returns to illegal activity against the earnings available in the legal sector. Readily accessible gig jobs raise legal earnings, thereby increasing the opportunity cost of crime.

[1] The Pew Research Center reports the following statistics in "The State of Gig Work in 2021:" Hispanics (16%), Blacks (10%), 18-29-year-olds (18%), and low-income earners (12%) versus Whites (4%), 30-49-year-olds (7%), and high-income earners (2%).

[2] See the EU Directive 2024/2831 on improving working conditions in platform work. In China, Meituan, a major delivery platform, uses 7.5 million riders who are paid $11 billion a year; see The Economist, 4 April 2025, last accessed August 2025.

The Beckerian economic deterrence mechanism resonates with the testimony of an ethnic minority migrant in France, who "needed work" and who felt 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).[3] A complementary mechanism for the reduction in crime is voluntary (self-) incapacitation: time spent working reduces the amount of unstructured time available for criminal activity. Delivery work, which often takes place during evenings and weekends, may therefore lower offending by reallocating time away from periods when opportunistic crime is most likely.

We study how food-delivery platforms affect local labor markets and crime in France, a country where disadvantaged youth and migrants face persistently high inactivity and unemployment (Cahuc et al., 2013; Glover et al., 2017). During our pre-pandemic observation period, from 2012 to 2019, unemployment was 8 to 14 percentage points higher for youth (15–24), immigrants, and low-skilled workers than for prime-age (25–49), natives, and high-skilled workers. We exploit the staggered rollout of Uber Eats and Deliveroo, the two largest food-delivery platforms in France.[4] Both platforms began operating in eleven areas in 2015 and then expanded sequentially. Identification relies on this staggered timing, which is plausibly exogenous conditional on market size. We compare "treated" areas—those where online platforms operated at a given point in time—with otherwise similar areas that will be treated later or never.

Our staggered difference-in-differences estimates show that platform entry leads to a sharp rise in delivery-worker registrations, with take-up concentrated among men and, in particular, migrant men. This first-stage response—measured using administrative registrations—identifies which demographic groups are most exposed to the arrival of gig work opportunities. We then examine whether this differential exposure translates into changes in local labor-market outcomes. Although aggregate unemployment and inactivity do not change significantly, labor-market activation is visible for the groups driving rider take-up: male unemployment declines, and inactivity falls markedly among migrant men in the years following platforms entry.

We next examine whether these labor-market adjustments translate into changes in criminal activity. We find that crime declines in jurisdictions where delivery platform gig jobs become available, consistent with both economic deterrence and voluntary inca-

[3] New York Times, 16 June 2019, last accessed July 2025.

[4] See https://dashmote.com/articles/the-ongoing-food-delivery-race-in-europe, last accessed July 2025.

pacitation mechanisms. First, low-skill and income-generating crime, such as street-level drug dealing and shoplifting, decline, suggesting that higher legal earnings raise the opportunity cost of illicit activities. Second, a reduction in violence against people and property destruction suggests a self-incapacitation channel, whereby delivery work keeps at-risk youth occupied during hours when offending is most likely. In contrast, skill-intensive property crimes, such as burglary and vehicle theft, do not show significant change. These offenses require more specialized skills, planning, and criminal networks insulated from the low-skill employment shock created by platform gig jobs.

A key identification check leverages the legal requirement that delivery workers must be at least 18 years old. Since many offenders cluster around this age cutoff, we test whether platform entry reduces crime only for the individuals legally eligible. Court records report the age of offenders, which allows us to estimate separate treatment effects for individuals just below and just above 18. If crime decreases only among those aged 18 and over, alternative explanations such as increased policing or the "eyes-on-the-street" effect of riders, are unlikely. These factors would also affect younger offenders. The data confirm that the decline in crime is concentrated among offenders aged 18 and older, indicating that access to delivery gig jobs, rather than other confounding factors, drives the observed reduction in criminal activity.

Our paper adds to several strands of the literature. First, existing work shows that digital platforms provide flexible jobs (Mas and Pallais, 2017; Chen et al., 2019) and offer a novel alternative for marginalized, low-skilled, or unemployed workers (Agrawal et al., 2015; Burtch et al., 2018; Huang et al., 2020; Laitenberger et al., 2023; Guo et al., 2024). In this paper, we provide causal evidence on how the rollout of low-barrier gig-job opportunities affects local labor-market attachment and area-level crime.

Second, our paper contributes to the extensive literature on job opportunities and crime (Becker, 1968; Grogger, 1998; Machin and Meghir, 2004; Draca and Machin, 2015; Hjalmarsson et al., 2024). We focus on changes at the extensive margin of legal employment access, studying how the arrival of low-barrier gig jobs alters behavior among individuals with weak attachment to the formal labor market. Delivery work, characterized by minimal screening and low entry costs, expands access to legal income opportunities for disadvantaged workers, which may help deter crime. This perspective complements recent work showing that restricted access to employment—due to discrimination against ethnic minorities or individuals with criminal records—can sustain labor-market exclusion and criminal involvement (Kline et al., 2022; Cullen et al., 2022).

Finally, our paper relates to recent work on digital platforms and crime. Prior work links ride-hailing availability to victimization outcomes: Uber's rollout in the United States raises auto-theft arrests but lowers assaults (Dills and Mulholland, 2018), with mixed effects on overall personal crime (Weber, 2019). A more recent study based on São Paulo shows that crime falls in areas where the iFood delivery platform expands (Frankenthal, 2025). We go beyond this evidence by studying a developed-country setting in which gig work constitutes formal employment and can be linked to administrative labor-market records and residential locations. This allows us to observe who takes up delivery work, where they live, and how expanded access to legal jobs for disadvantaged populations translates into changes in labor-market attachment and criminal behavior. In addition, the legal minimum age for delivery work creates a sharp eligibility threshold that allows us to isolate the causal effect of job access on offending from alternative channels such as probability of detection or shifts in consumer behavior. Our conceptual framework further predicts heterogeneous effects across offenses, with some crimes responding to improved job access, whereas others should not.

Importantly, we do not claim that gig jobs are a comprehensive solution to crime or labor-market exclusion. Rather, our focus is on the margin of access: we show that lowering entry barriers to legal income—even through temporary, flexible, and low-wage work—can generate meaningful behavioral responses among individuals at the boundary between legal and illegal income opportunities.

The paper is organized as follows. Section 2 describes the labor market context and presents the main insights of our conceptual framework. Section 3 documents the rollout of food delivery platforms in France and explains the requirements to access gig work. Section 4 characterizes the demographic profile of delivery riders using administrative data. Section 5 presents our empirical strategy and estimation approach. Section 6 reports the main results on the labor market and crime outcomes. Section 7 provides evidence on mechanisms and robustness checks. Section 8 concludes.

2 Labor Market Exclusion, Gig Work, and Crime

2.1 Labor Market Exclusion and Crime

A large economic literature documents a close relationship between labor market exclusion and crime. In France, unemployment and inactivity remain disproportionately high among young people and individuals of immigrant origin, groups that are also overrepresented in the criminal justice system. Between 2012 and 2019, youth unemployment (ages 15-24) averaged 22.7%, while first- and second-generation migrants experienced unemployment rates of 15.9% and 13.7%, respectively, compared to 8.1% among natives.[5] Appendix Figure A2 and Tables A1 and A2 summarize unemployment and inactivity rates by age and geographic origin in France. The observed disparities reflect both differences in skills and continued demand-side barriers to employment.

Evidence from correspondence studies shows that hiring discrimination remains substantial in France: applicants with North African-sounding names receive 30-45% fewer callbacks than otherwise identical candidates (Breda et al., 2021). This ethnic penalty declines with job qualification, implying that discrimination is most severe in low-skill segments of the labor market, where many young men of immigrant background with weak or disrupted employment histories are concentrated. These labor market patterns mirror the demographic composition of offenders. When delivery platforms entered the French market in 2015, 67% of convicted individuals were between 18 and 40 years of age and 89.8% were male.[6]

Taken together, these facts point to a tight overlap between groups facing persistent labor market exclusion and those most exposed to criminal involvement. As a result, market developments that expand access to legal employment at the lower end of the skill distribution may have important implications for crime.

2.2 Gig Work as Low-Barrier Legal Employment

By bypassing conventional recruitment channels, food-delivery platforms relax multiple constraints to employment. For riders, entry costs are low, required skills are minimal, and hiring decisions are not mediated by subjective assessments of past employment

[5] Author's calculations based on INSEE data.

[6] French Ministry of Justice data. Comparable age and gender patterns are observed in the United States.

histories. Beyond basic equipment and administrative registration, access does not depend on formal qualifications, interviews, or résumé-based screening. Gig job entry is fast, involves little job search, and relies minimally on employer discretion. These features sharply distinguish delivery gig work from standard low-skill jobs, where hiring frictions, screening, and discrimination can exclude individuals with limited education, weak labor-market attachment, or criminal records.

Evidence from related platform settings supports the view that platforms relax traditional hiring constraints. For example, Lambin and Palikot (2022) show that reputation-based mechanisms in ride-sharing platforms attenuate ethnic penalties in customer evaluations. More broadly, self-employment and gig work are used disproportionately by individuals with criminal justice involvement, consistent with their limited reliance on formal screening (Finlay et al., 2023). Complementary evidence from record-remediation policies shows that even after formal criminal-record barriers are removed, regular wage employment responds little—likely because disrupted employment histories remain a stigma—whereas participation in platform-based gig work increases sharply (Agan et al., 2024). Together, these findings suggest that gig jobs remain accessible precisely when traditional employment opportunities are constrained.

The central feature of gig work in this context is accessibility rather than job quality. By lowering barriers related to skills, screening, discrimination, and prior employment records, delivery platforms expand access to legal income opportunities. Our conceptual framework, formalized in Appendix A, illustrates how the arrival of gig opportunities affects the trade-off between legal and illegal work for low-skilled individuals by lowering barriers to legal employment. As access to legal work improves, the expected utility of legal activity increases relative to illegal alternatives, implying that higher illicit returns are required for crime to remain attractive.

Two mechanisms are central in this framework. First, in the Beckerian deterrence mechanism (Becker, 1968), readily accessible gig jobs raise expected legal earnings and reduce uncertainty about immediate legal income, thereby increasing the opportunity cost of crime—even when work is taken up intermittently or at low intensity. Second, voluntary (or self-) incapacitation operates through time allocation: time spent working reduces opportunities to engage in offending. This mechanism has been documented in settings where participation in time-absorbing activities crowds out criminal behavior, including schooling (Jacob and Lefgren, 2003), movie attendance (Dahl and DellaVigna, 2009), and large sporting events (Marie, 2016).[7] Importantly, these mechanisms do not require full labor-market activation. The defining feature of gig jobs is that they can be combined with schooling, informal activity, or other employment, so even partial, irregular engagement can alter time use and raise the relative attractiveness of legal income.[8]

3 Platform Rollout and Access to Gig Work

3.1 Platform Rollout

Uber Eats and Deliveroo are the two dominant food-delivery platforms in France. Both entered the French market in 2015, initially launching in large metropolitan areas such as Paris and Lyon, before progressively expanding to smaller cities and peri-urban areas. The expansion of the platform was rapid and geographically staggered, generating substantial variation in the timing of entry across local markets (Appendix H shows the year of platform rollout in the 15 largest cities in France).

The platforms organized their expansion around what they refer to as *reference areas*: spatial units defined by the joint availability of restaurants (supply), consumers (demand), and potential riders. These areas are not limited to administrative city boundaries and may encompass multiple municipalities, including suburban neighborhoods. As declared by Uber Eats France's Head of Expansion, platform entry decision in a given area is based on local population density, the restaurant base, and the pool of potential riders.[9] This supports the interpretation of platform rollout as plausibly exogenous conditional on population. Importantly for identification, platform entry is not subject to binding regulatory constraints and is therefore primarily driven by market size rather than local labor-market or crime conditions.

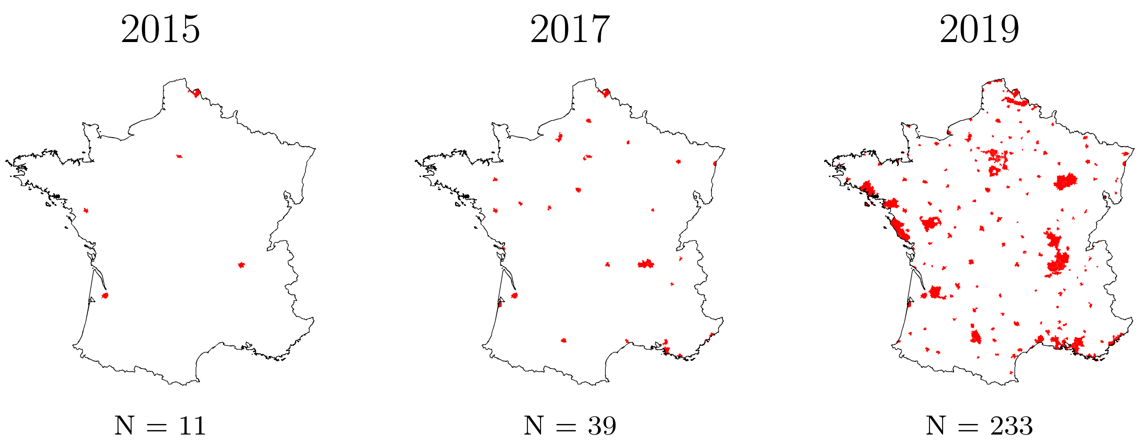
By 2019, Uber Eats and Deliveroo operated in 2,114 reference areas, covering more

[7]In some of these settings, crime reductions coexist with concentration effects, whereby aggregating individuals with elevated baseline offending risk or heightened arousal in the same place can increase violent interactions. This concern is less relevant in our context: delivery work is individually performed, spatially dispersed, and does not generate dense peer interactions.

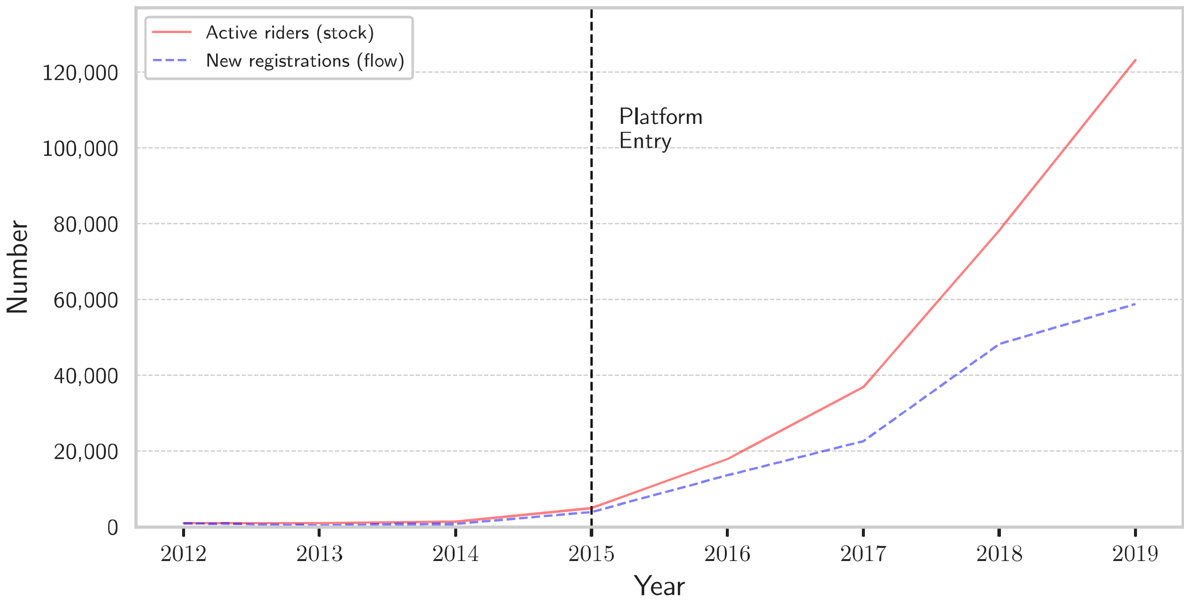
[8]Although we do not observe working hours directly, this flexible form of labor-market attachment is consistent with the patterns documented in the data and complements the access-based mechanisms emphasized here.

[9]To the question "How does Uber Eats select the cities in which it operates?" Pierre Estagnasié, Head of Expansion for Uber Eats France, answered: "nous étudions les bassins de populations, la base de restaurants et le réservoir de coursiers autour de chaque ville." See actu.fr, last accessed December 2025.

Figure 1: Platform Rollout and Food-Delivery Workers in France



Panel A: Platform Rollout by Year and Police Jurisdiction, 2015–2019



Panel B: New Registrations (Flow) and Active Riders (Stock), 2012–2019

Notes: Panel A displays the staggered rollout of major food-delivery platforms across France between 2015 and 2019, aggregated at the level of police jurisdictions. Red color indicates the first year of platform entry. Number of police jurisdictions where platforms operate: 11 (2015), 29 (2017) and 223 (2019). Panel B shows annual counts of food-delivery workers. The dashed line reports new registrations (the annual inflow of newly registered riders). The solid line reports the stock of active riders, defined as registered micro-enterprises that have declared positive turnover in at least one of the previous two years. The vertical dashed line marks the entry of major food-delivery platforms in 2015. See Appendix Figure A3 for the number of riders and ride-hailing drivers after 2019.

than half of the French population. Panel A of Figure 1 maps the staggered rollout of the platforms between 2015 and 2019, aggregated at the level of police jurisdiction, which constitutes our main spatial unit of analysis. Our sample includes 681 police jurisdictions, the most granular level at which crime data are consistently observed (see Appendix E for data construction). Panel B shows the evolution of new registrations of self-employed workers in food delivery and the stock of active riders, defined as registered micro-enterprises that have declared positive turnover in at least one of the previous two years (see Section 4 for details on registration status and income reporting).

Platform entry also requires the participation of local restaurants. Only restaurants located within a covered area can join a delivery platform and receive orders. Participation is voluntary and involves a simple application process and brief training on platform-specific software; once approved, orders are managed through a tablet interface provided by the platform. Consumers similarly face minimal friction, needing only to download the app and provide basic information to place an order.

Importantly, the expansion of food-delivery platforms did not face organized resistance from incumbent firms. Unlike the entry of ride-hailing services into regulated taxi markets, which triggered protests and attempts to block entry in some areas,[10] restaurants generally welcomed platform access as a source of additional demand. As a result, platform rollout proceeded smoothly within covered areas and translated directly into expanded access to delivery services and gig work, without evidence of local backlash or regulatory obstruction.

Having described how food-delivery platforms entered local markets, we now turn to the institutional conditions governing access to delivery work—that is, who can become a rider once a platform operates in an area.

3.2 Legal Access and Conditions of Delivery Work

Food-delivery platforms impose only a small number of clear and binding requirements. Riders must be at least 18 years old, present valid identification (EU passport or residence permit), and register as self-employed—a free and straightforward procedure in France. Entry also requires a smartphone and the purchase of a branded delivery bag. For bicycle delivery, the most common mode during our period of study, no license, cer-

[10] See, for example, Politico Europe, "France braces for new taxi–Uber war", 26 January 2016.

tification, or formal training is required, keeping both financial and administrative entry costs low. Legal constraints related to criminal records are relatively light. Riders must not have serious convictions, but less severe offenses do not disqualify applicants.[11] As a result, individuals with prior convictions that would exclude them from many regulated or screened occupations can access food-delivery work once eligibility conditions are met.

These requirements stand in sharp contrast to those governing other platform-based transport services. To operate as a ride-hailing driver in France, applicants must present clean criminal records,[12] complete mandatory training, and bear substantially higher capital costs, including access to a suitable vehicle. These additional legal, financial, and administrative barriers exclude individuals with misdemeanor convictions, recent criminal justice involvement, or limited resources. Food delivery therefore remains accessible to a much broader segment of the population, including young adults and individuals facing legal or reputational barriers in alternative gig or wage employment.

Because undocumented migrants cannot legally register as self-employed, a shadow market has emerged in which rider accounts are rented or shared. Platforms actively attempt to limit such practices. For example, Uber Eats suspended approximately 2,500 accounts in 2022.[13] The persistence of this shadow market points to excess demand for delivery work among individuals who lack legal status. For our analysis, this implies that platform entry may affect crime through increased access to delivery work even if some of this activity is not fully recorded in administrative employment statistics. Crime outcomes capture behavioral responses within treated areas regardless of the legal status of workers. This reinforces the relevance of combining labor-market and crime outcomes to assess the local impact of platform entry.

Delivery work offers flexible scheduling and piece-rate compensation. Although work intensity and earnings vary substantially across locations, platforms, and individuals, *survey evidence* suggests that between 2015 and 2019 riders could earn hourly revenues comparable to, or slightly above, the minimum wage, typically in the €10-15 range (Dau-

[11] France maintains three nested criminal-record extracts ("bulletins") that differ in scope and accessibility (see service-public.gouv.fr). Bulletin B1 is the full criminal record, accessible only to judicial authorities. Bulletin B2 is a restricted extract available to certain employers and public bodies. Bulletin B3 is the most selective extract and is the only one individuals can obtain themselves. B3 includes only the most serious convictions. Food-delivery platforms require a clean B3 record. Consequently, individuals with prior convictions recorded on B2 are barred from many occupations, but as long as those convictions do not appear on B3, they remain eligible for platform delivery work.

[12] They must present clean B2 and B3 records, see footnote 11.

[13] See Le Parisien, 3 October 2022, last accessed July 2025.

gareilh, 2022; Dablanc et al., 2019).[14] Earnings are an important dimension for assessing the long-run viability and career prospects of platform work, particularly given the income volatility and limited progression paths documented for solo self-employment and gig jobs (Boeri et al., 2020). We focus instead on access to legal income opportunities rather than earnings dynamics. This emphasis reflects both the central role of labor-market participation margins for the populations we study and data constraints. In particular, we do not observe hours worked, which vary widely among riders. Moreover, administrative earnings records for micro-entrepreneurs are incomplete and distorted because many riders report no revenue or very low turnover, which is consistent with documented evasion of taxes and social security contributions.[15] Focusing on whether individuals work at all, rather than on how much they earn conditional on working, is therefore both empirically credible and relevant for understanding labor-market attachment and its potential implications for crime.

4 Riders

To characterize who the delivery riders are and where they come from, we combine three complementary administrative sources from INSEE: the *Sirene* business registry, the Self-Employed Database (*Base Non-Salariés*), and the All Active Workers Panel (*Panel Tous Actifs*). Together, these data allow us to document riders' demographic profiles, geographic location, and labor-market attachment prior to entry into delivery work (see Appendix I.1 for details on data construction and coverage).

4.1 Who Are They? Demographic Characteristics

We begin by describing the demographic characteristics of delivery riders. The *Sirene* database lists 153,322 unique individuals registered under NAF code 53.20Z (*Other postal and courier activities*) between 2012 and 2019.[16] As shown in Panel B of Figure 1, new registrations under this code rise sharply from 2015 onward, coinciding with the entry

[14] In 2018, Uber Eats cited €10–15 per hour and Deliveroo reported an average of €13 (see New York Times, 16 June 2019).

[15] See Les Echos, 14 December 2022 and 23 November 2021, last accessed January 2026.

[16] Registrations under code 53.20Z were rare prior to the arrival of delivery platforms. While this code may also capture other courier activities, the timing and magnitude of the increase strongly suggest that it is driven by platform-based food delivery.

and rapid expansion of food-delivery platforms, reaching about 60,000 new riders per year and a stock of roughly 130,000 active riders by 2019. Appendix Figure A3 compares this evolution to ride-hailing registrations and extends the series beyond 2019, showing that ride-hailing remains a quantitatively small margin in this market, while food-delivery work expands dramatically in the years that follow. This indicates that delivery—not ride-hailing—constitutes the relevant margin of gig-job creation in our estimation window, and that food-delivery platforms represent a potentially important component of low-skilled labor markets once conditions stabilize after the pandemic.

To shed light on riders' likely backgrounds, we use first names recorded in *Sirene* to infer broad geographic name origins.[17] Using a probabilistic classification approach based on large language models (see Appendix D), we estimate that 48.6% of riders have a non-European-sounding first name, the vast majority of which are classified as Arabic-sounding. Although name-based inference is necessarily imperfect, these patterns suggest a strong overrepresentation of individuals likely to face discrimination in the labor market.

We complement this information with the *Base Non-Salariés*, which reports age, gender, place of birth, and municipality of residence for self-employed workers. This source identifies 147,923 unique riders aged 16-54 during the period 2012-2019, of whom 97% also appear in the *Sirene* data. Riders are overwhelmingly male (93%) and young, with an average age at first registration of 25 years (s.d. 6.6). About 32% are foreign-born.[18]

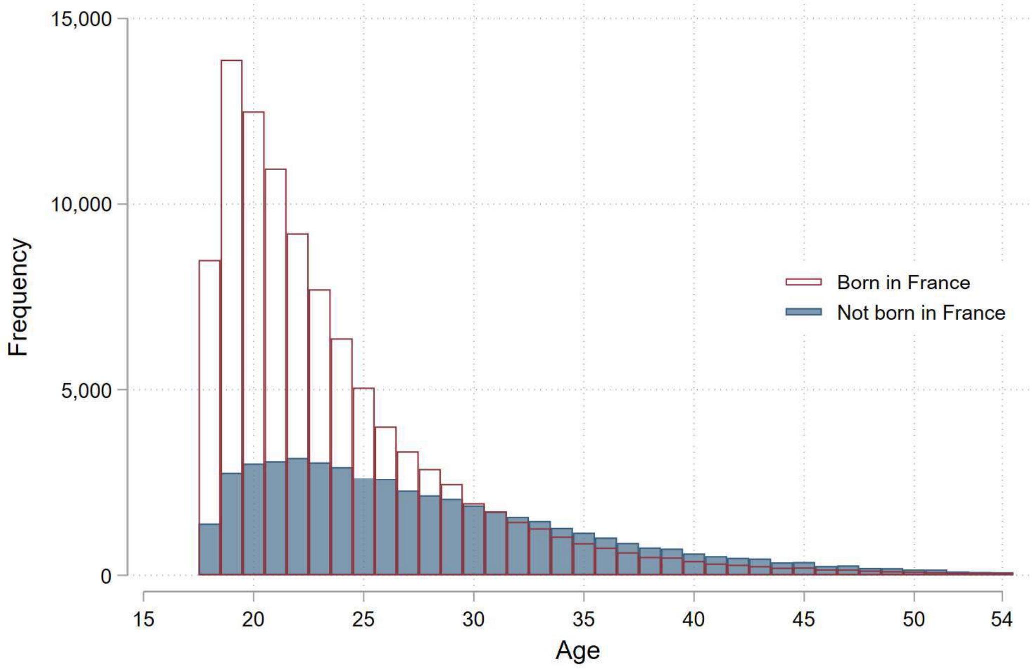
Figure 2 plots the age distribution of riders by nativity. French-born riders are highly concentrated in the 18–24 age range, with participation declining sharply thereafter. In contrast, foreign-born riders display a flatter age profile, indicating more persistent engagement in delivery work beyond early adulthood.

These descriptive statistics, complemented by survey evidence reported in Appendix Table A3, point to a clear rider profile. Riders are predominantly young men, with a substantial share of foreign-born individuals and, among those born in France, a high prevalence of non-European-sounding names. These patterns are consistent with the view that

[17] We exclude observations without a recorded first name (37,612) and drop unique first names that could allow identification (12,929), following INSEE anonymization guidelines.

[18] French administrative data do not permit the construction of ethnic or ancestry-based statistics, even when names are available, so administrative records can only distinguish individuals born in France from those born abroad. As a result, second-generation immigrants, who face substantial discrimination and barriers in the French labor market (see Section 2.1), cannot be separately identified in these data. Our name-based measures therefore provide complementary evidence on the likely ethnic and second-generation composition of the rider population.

Figure 2: Rider Age by Nativity (Foreign vs. French-born)



Notes: Age distribution of riders by nativity (foreign vs. French-born). The sample includes 147,963 riders registered as micro-entrepreneurs (code 53.20Z) between 2012 and 2019. "Born in France" (hollow bars, $n = 100{,}128$) denotes riders born in France. "Not born in France" (filled bars, $n = 47{,}835$) includes all foreign-born riders. Age is measured at the time of registration and the sample is restricted to riders aged 15–54 with valid birthplace information.

food-delivery platforms disproportionately attract individuals from groups facing weaker attachment to the formal labor market and greater barriers to standard employment.

4.2 Where Do They Come From? Spatial and Labor-Market Origins

Beyond individual characteristics, riders are unevenly distributed across space. Using geolocation information from the *Sirene* dataset, we compare the residential location of riders to that of the general population across neighborhoods and cities, along several socioeconomic dimensions, including income, education, unemployment, and inactivity (see Section 5.3 for definitions).

Riders are disproportionately concentrated in disadvantaged areas. Table 1 shows that in 2019, 15.3% of riders lived in "Priority Neighborhoods", compared with 9.8% of the overall population.[19] Riders are likewise overrepresented in cities characterized by

[19]Priority Neighborhoods (or *Quartiers prioritaires de la politique de la ville* in French) were established by the 2014 planning law on urban affairs and cohesion to reduce spatial inequalities. Their boundaries

low income per capita, low educational attainment, high immigration rates, and elevated male unemployment, inactivity, and welfare receipt. These spatial patterns reinforce the individual-level evidence that delivery work attracts populations facing weaker labor-market opportunities.

Table 1: Rider Representation Across Disadvantaged Areas

	% of Population	% of Riders
Priority Neighborhoods[a]	9.80	15.29
Cities by[b]		
Low-income per capita (bottom 5%)	9.78	13.66
Low-education (bottom 5%)[b]	4.46	6.94
Immigrant rate (top 5%)	18.22	40.93
Male unemployment rate (top 5%)[c]	9.98	11.45
Inactivity rate (top 5%)[c]	8.23	9.63
Welfare claimant rate (top 5%)[c]	9.50	10.27

Notes: [a]Priority Neighborhoods (*Quartiers prioritaires de la politique de la ville*) are areas characterized by a high concentration of low-income households. Some riders could not be precisely geolocated within cities and are not included in the QPV estimates. The analysis includes only cities with more than 2,000 inhabitants (5,280 in total) and uses rider counts from 2019. [b]Low education refers to the share of individuals without a diploma or, for those who left school before 1989, without a Primary School Certificate (*Certificat d'Études Primaires*). [c]Unemployment, inactivity, welfare claimant and crime rates are based on 2014 population data to avoid contamination effects, since more gig jobs would result in lower rates.

Next, we examine the riders' labor-market position prior to entering delivery work. Using the *Panel Tous Actifs* (All Active Workers Panel; see Section I.1.3), a representative one-eighth sample of the French workforce, we identify 16,805 individuals who created a micro-enterprise without employees after 2015 under activity code 53.20Z.

Table 2 reports labor market status in the month prior to registration. Entry into delivery work occurs predominantly from outside regular employment. More than half of the 16,805 identified riders (52%) are not observed in administrative employment records in the month before registration. Among them, 94% have no employment history recorded at any point in the panel, indicating direct entry into delivery from inactivity or from outside formal employment rather than job-to-job transitions.

Among riders with observed prior activity, only a minority held stable jobs: 25% were employed full-time, 13% part-time, and 9% were registered as unemployed in the preceding month. Survey evidence further suggests that, for a non-negligible share of

are defined by the National Agency for Territorial Cohesion based on concentrations of low-income households. As of January 2015, there were 1,514 Priority Neighborhoods across 859 cities.

riders, delivery work represented the only feasible employment option at the time of entry (see Appendix C).

Table 2: Previous Employment Status of Riders

	Number		Share (%)	
Full-time employed	4,222		25.1	
Part-time employed	2,232		13.3	
Unemployed	1,588		9.4	
Already self-employed[a]	63		0.4	
Not observed in prior month[b]	8,700		51.8	
of which:				
Not previously employed		8,201		94.3
Previously employed (ever)[c]		499		5.7
Total	16,805	8,700	100.0	100.0

Source: All Active Workers Panel (*Panel Tous Salariés*), a one-eighth representative sample of the French workforce. Notes: Riders' status in the month preceding creation of self-employment under activity code 53.20Z. [a] It includes self-employed, home workers, and a small number of individuals with missing employment status. [b] It indicates no record in the administrative source in the month before registration; most of these individuals have no prior employment history observed in the panel. Percentages in main rows are shares of the full rider sample. Percentages in the indented "of which" rows are compositions within the "Not observed in prior month" subgroup.

Despite the smaller absolute sample size inherent to a one-eighth administrative panel, these patterns are highly informative about the relevant margins of adjustment. They indicate that food-delivery platforms primarily draw workers from inactivity and weak labor-market attachment, rather than reallocating workers from existing jobs.

This evidence directly informs our analysis of the effects of platform entry on the labor market. Because new riders disproportionately come from outside regular employment, the primary labor-market responses to platform entry are expected to be reductions in inactivity and unemployment. Accordingly, our empirical analysis focuses on these margins, which best reflect the pre-entry status of individuals taking up delivery work.

5 Empirical Strategy and Outcome Measurement

5.1 Identification Strategy

We examine how the staggered rollout of food-delivery platforms across France affects labor-market activation and crime. Our identification strategy exploits variation in the timing of platform entry across areas and relies on a staggered difference-in-differences

(DiD) design:

$$Y_{zt} = \alpha_z + \lambda_t + \sum_{\tau=-7}^{4} \beta_\tau \text{Entry}_{zt}^{\tau} + \epsilon_{zt}, \tag{1}$$

where Y_{zt} denotes the outcome of interest—rider supply, labor-market outcomes, or crime rates—in year t and area z (defined below). Entry_{zt}^{τ} is an event-time indicator equal to one if year t is τ years relative to the first entry of a food-delivery platform in area z. We include area fixed effects α_z to absorb time-invariant differences across areas and year fixed effects λ_t to control for common aggregate shocks.

Our main estimates are obtained using the staggered DiD estimator of Callaway and Sant'Anna (2021), which is designed to accommodate treatment-effect heterogeneity across cohorts and over time. This estimator constructs group-time average treatment effects using not-yet-treated and never-treated units as appropriate comparison groups, thereby avoiding the negative-weight and contamination issues that can arise in two-way fixed effects models with staggered adoption.

To assess the robustness of our findings, we also report results using the estimator of de Chaisemartin and d'Haultfœuille (2025) and alternative approaches to staggered DiD. These include a conventional OLS two-way fixed effects estimator and the interaction-weighted two-stage estimator of Gardner et al. (2024). Taken together with these estimators and specifications, our design allows us to trace how access to gig work changes labor-market attachment and how those changes translate into subsequent crime dynamics in a way that is robust to heterogeneous treatment effects and staggered adoption.

5.2 Treated Areas, Spatial Aggregation, and Spillovers

A key element of our empirical strategy is the definition of the treated area z, which must reconcile platform entry, labor-market outcomes, and crime measured on different spatial scales. Platform entry is observed at the municipality level, whereas crime and labor-market indicators are recorded at the level of police jurisdictions, the most granular unit for crime statistics in France.[20] Each municipality maps to exactly one police jurisdiction, but jurisdictions typically span multiple municipalities. Our data include 681 police jurisdictions, each covering on average about 50 municipalities.[21]

An empirical challenge is that not all municipalities within a given jurisdiction are

[20] See Appendix Figure K for an illustration of the geographical units.

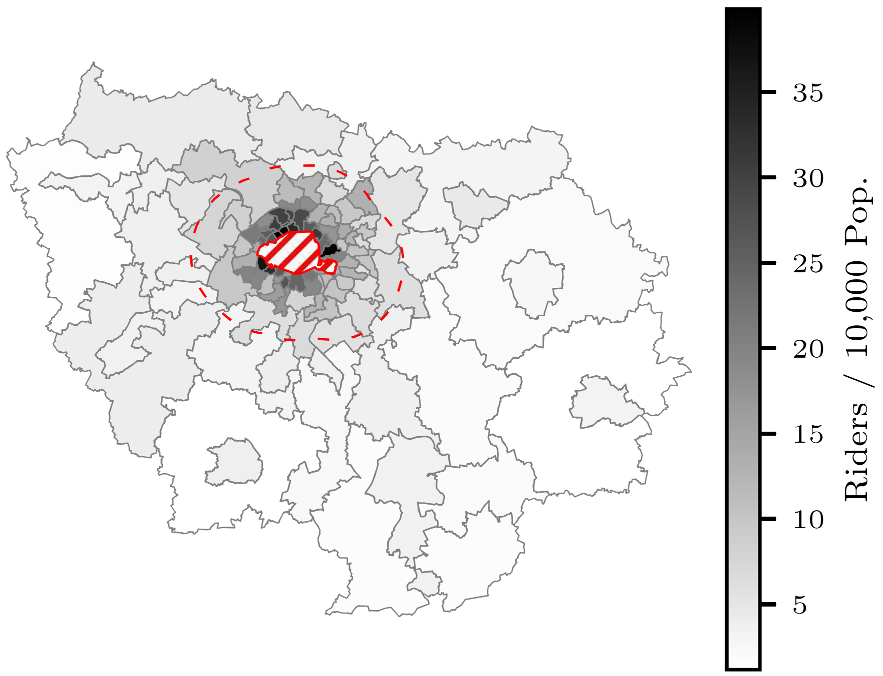
[21] In France, 88% of municipalities are rural or small with fewer than 2,000 inhabitants.

treated simultaneously. We therefore define a police jurisdiction as treated in the year in which the first municipality within its boundaries experiences platform entry. This timing typically coincides with entry into the most populous municipality in the jurisdiction, which platforms target as their primary reference market. This definition captures when residents of the jurisdiction first gain access to platform-based gig-work opportunities.

A further challenge is that riders may live, work, and potentially engage in criminal activity in different locations. In particular, individuals may reside in one municipality while delivering food or offending in nearby areas. To account for such spatial spillovers, we allow platform entry to affect outcomes beyond municipal boundaries by defining treatment exposure using a 15-kilometer buffer around each police jurisdiction. In robustness checks, we vary the size of the buffer. Using smaller buffers yields estimates that are noisier and less precisely estimated, though generally of similar sign and magnitude (see Appendix Tables A15 and A16). This pattern is expected: rider residence is much more dispersed than platform service areas. Many riders live in jurisdictions without active platform operations but commute to nearby treated areas. Treating these jurisdictions as controls when using smaller buffers introduces attenuation by misclassifying exposed populations as untreated. The 15-kilometer buffer strikes a balance between capturing economically relevant exposure to gig work opportunities and avoiding contamination of the control group. A smaller buffer would miss nearby jurisdictions whose residents can access platform work by commuting, whereas a larger buffer would classify many weakly exposed jurisdictions as treated and blur the treated–control comparison.

As an illustration, Figure 3 maps the police jurisdiction of Paris (red hatched area) and surrounding jurisdictions. Deliveroo and Uber Eats operated in Paris from 2015, but the service is based on riders who also reside in nearby suburbs and commute to the city. Rider density is especially high in the darker suburban jurisdictions, measured as riders per 10,000 residents. To capture Paris's catchment area, the figure also displays a 15-km buffer around Paris (red dashed line). Appendix Table A7 reports average demographic characteristics, labor-market indicators, and crime rates for police jurisdictions that are eventually treated and those that are never treated, measured in 2014 and 2019. Treated jurisdictions are substantially larger, reflecting the fact that platforms enter more populous areas first. By 2019, delivery-worker registrations are markedly higher in treated jurisdictions, while other labor-market and crime measures are broadly similar, with only

Figure 3: Riders in the Surrounding Area of Paris (2016)



Notes: The red hatched area denotes the police jurisdiction of Paris; surrounding areas are neighboring jurisdictions. Shading reports rider density (riders per 10,000 residents aged 15-54) in 2016, with darker areas indicating higher density. Paris is omitted from the color scale to improve contrast for nearby jurisdictions and to highlight potential spillover effects; within Paris, rider density is about 50 per 10,000 residents aged 15-54. The red dashed line shows the 15-km buffer used to define Paris's catchment area.

modest differences.

These descriptive patterns are informative about the types of areas platforms enter, but our identification does not rely on level comparisons. Instead, it relies on a parallel trends assumption in the absence of treatment. We will assess the plausibility of this assumption by examining pre-entry dynamics.

5.3 Rider Supply, Labor-Market, and Crime Measures

We examine how the rollout of food-delivery platforms affects rider supply, local labor-market conditions, and crime. Rider supply captures the most immediate response to entry, by indicating whether platforms attract workers. Labor-market outcomes measure broader activation along unemployment and inactivity margins, while crime outcomes reflect downstream behavioral responses. All outcomes are aggregated annually at the police-jurisdiction level, the spatial unit used in administrative crime statistics. Our analysis covers 681 police jurisdictions between 2012 and 2019, yielding a balanced panel of 5,448 jurisdiction-year observations.

Rider Supply. We measure rider supply using administrative business records of self-employed micro-entrepreneurs operating under food-delivery activity codes (see Section 4 and Appendix I). For each police jurisdiction and year, we compute the annual stock of active riders, weighting each registration by its presence rate over the year using observed dates of business creation and closure. The data also allow us to disaggregate rider supply by gender and nationality (French-born versus foreign-born), enabling us to examine whether platform entry differentially attracts workers from groups that are more represented among delivery riders.

Labor-market: Unemployment and Inactivity. Labor-market and population indicators come from INSEE administrative statistics on the population census.[22] The data allow us to track unemployment and inactivity, two distinct margins that matter in a context where gig work attracts individuals with weak prior attachment to the labor market. In the empirical analysis, we report effects for the overall working-age population and then by gender and nationality. This disaggregation aligns the measurement of labor-market activation with the demographic composition of delivery riders, which, as documented below, is heavily concentrated among men and individuals of migrant origin.

We measure the unemployment of specific groups using the unemployment share, defined as the number of unemployed individuals in a group divided by the group population. Unlike the standard unemployment rate, this measure isolates variations in unemployment from shifts in labor force participation (i.e., inactivity). We measure the inactivity of a group as the number of inactive members, excluding students and (pre-)retirees, divided by the group population. This restriction ensures that the analysis focuses on the population available to participate in the labor market.

Crime: Police and Courts. We draw on two complementary administrative sources to measure criminal activity (see Appendix I).

- *Police-recorded offenses.*[23] Data from the Ministry of the Interior are available at the police-jurisdiction level and follow the *État 4001* classification, covering property crimes (e.g., theft and burglary), drug-related offenses (e.g., possession and dealing), and violent crimes (e.g., assault). The data allow us to study how platform entry

[22] See Employment and Labor Force Participation in 2019 - Population Census.
[23] The data can be downloaded from DataGouv.fr (last updated February 1, 2022). See Appendix I.2.1.

affects overall crime and specific offense categories. We focus in particular on offenses plausibly responsive to changes in low-skill legal income opportunities, such as shoplifting, drug possession, and minor theft.

- *Court records and age-based eligibility.*[24] To exploit the legal minimum age requirement for platform work, we complement police data with case-level court records that report the age of the offender at the time of the offense. These data have a narrower scope, excluding the most severe offenses and dismissals, but they allow us to compare crime responses for individuals just below and just above the minimum age threshold for gig work. This age-based comparison provides a key test of whether crime changes operate through labor-market access, rather than through mechanisms that would affect offenders of all ages.

Together, these three outcomes, rider supply, labor-market activation, and crime, capture key margins along which platform entry may affect behavior, from the immediate take-up of gig work to broader labor-market responses and changes in criminal activity. This structure guides the presentation of our main results.

6 Main Results

6.1 Platform Entry and Rider Supply

We begin by examining how the arrival of food-delivery platforms affects the number of riders registering in treated areas. To assess whether entry translates into rider take-up, we estimate event-study specifications tracing changes in rider registrations relative to the year of platform entry.[25]

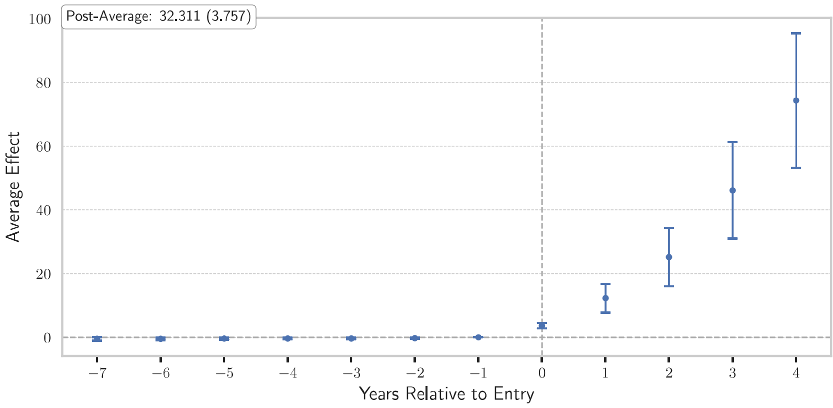
Figure 4 shows a clear increase in rider registrations following platform entry, but the response is not immediate. Rather than a sharp jump at event time 0, registrations rise gradually over subsequent years. This pattern indicates that the availability of gig-work opportunities diffuses over time, as information spreads and workers progressively take up platform jobs. This gradual adjustment is consistent with the institutional features

[24]See Appendix I.2.2 for details.

[25]Rider registrations are identified using the NAF activity code 53.20Z (*Other postal and courier activities*), which predates the arrival of food-delivery platforms and was already available to micro-entrepreneurs prior to 2015. Take-up under this code was limited before the expansion of platform-based food delivery (see Figure 1).

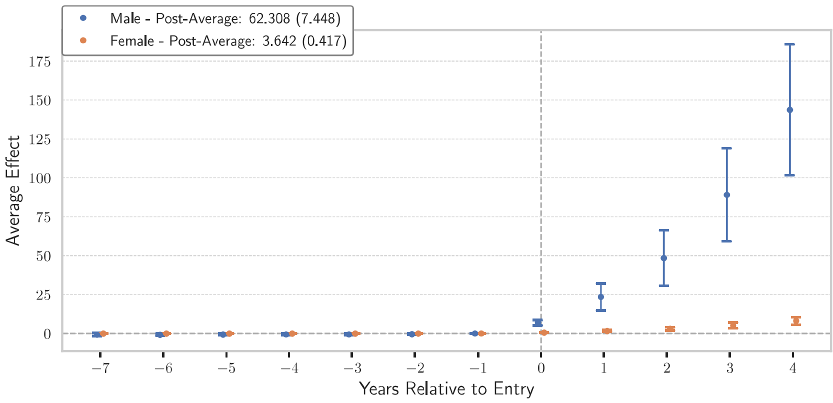
Figure 4: Impact of Platform Entry on *Rider Registrations*

A. Overall



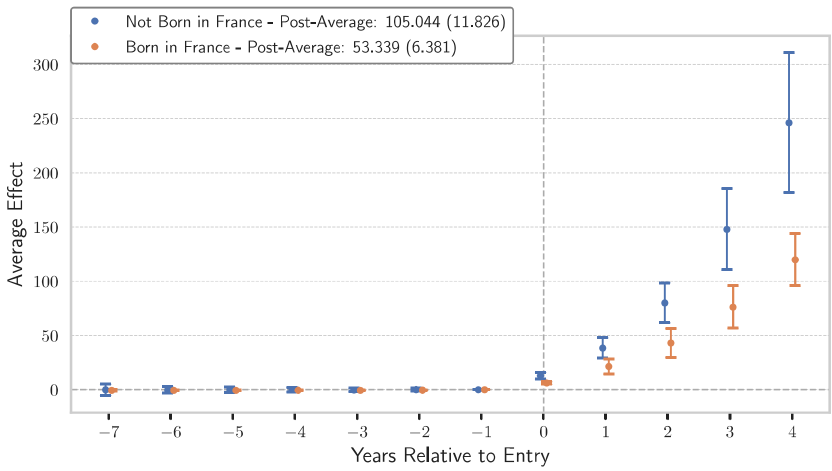
Post-entry average per 10,000: +32 riders

B. Male vs. Female



Post-entry average per 10,000: Male: +62; Female: +4

C. Male: Foreign-born vs. French-born



Post-entry average per 10,000: Foreign: +105; French: +53

Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. The vertical dashed line marks event time 0. Outcomes are annual rider registrations per 10,000 residents aged 15-54: Panel A: all riders; Panel B: sex-specific rates (per 10,000 men and women); Panel C: nativity-specific rates (per 10,000 foreign- and French-born residents). Post-entry values are averages across all post-entry years. Standard Errors are clustered at the police jurisdiction level. 95% confidence intervals shown.

of platform rollouts. Following entry into a new area, platforms typically invest in rider recruitment through targeted promotion, onboarding assistance, and in-kind incentives such as free delivery bags and support with registration. Even when formal entry costs are low, awareness and coordination take time to build.

Once uptake begins, growth is sustained. On average, platform entry leads to an increase of approximately 32 registered riders per 10,000 working-age residents in the post-entry period (Panel A). This aggregate effect, however, masks substantial heterogeneity across demographic groups. Panel B shows that registrations rise almost exclusively among men: rider supply increases by roughly 62 per 10,000 male residents, compared to only about 4 per 10,000 female residents. Panel C reveals a similarly uneven response by nativity of male riders. Among the foreign-born, platform entry increases rider registrations by approximately 105 per 10,000 foreign-born male residents, whereas the corresponding increase among the French-born is about 53 per 10,000. These magnitudes indicate that platform expansion disproportionately attracts workers from groups with weaker attachment to the formal labor market, men and migrants in particular, while take-up among women is minimal. Importantly, all effects are scaled relative to the size of each group's population, so the stronger responses reflect genuinely higher participation rates rather than differences in group size.

Across all panels, pre-entry coefficients are flat and statistically indistinguishable from zero, supporting the parallel trends assumption. The absence of pre-trends, combined with the gradual post-entry buildup in registrations, supports an interpretation of platform rollout as a plausibly exogenous increase in access to low-barrier legal work that operates through recruitment and diffusion rather than immediate labor-market reallocation.

6.2 Labor Market Outcomes

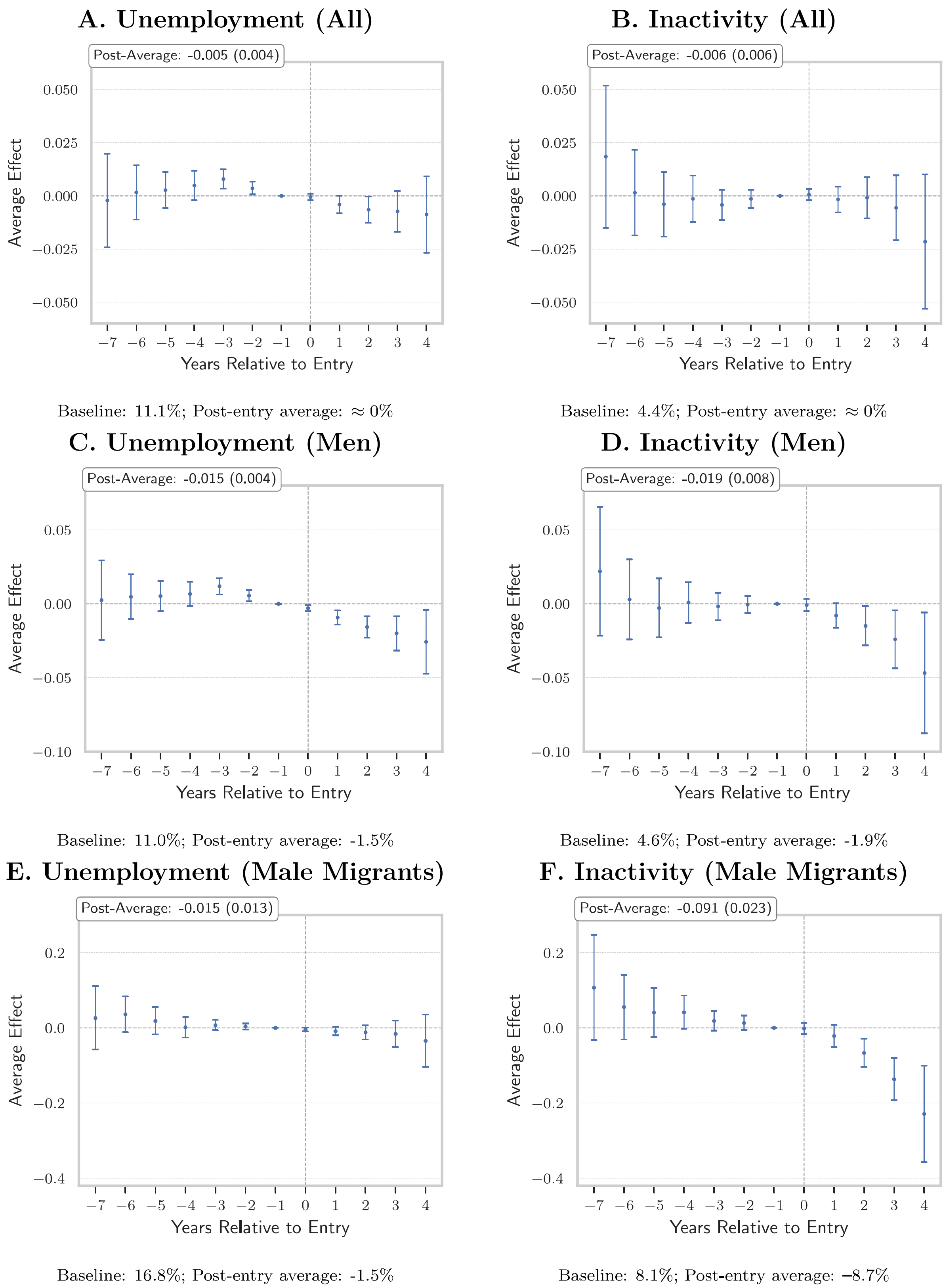
We now examine whether the expansion of platform-based gig work translates into broader changes in local labor-market conditions. Since platform entry increases rider registrations by roughly 32 per 10,000 working-age residents, the scale of this shock is modest relative to the size of local labor markets. It is therefore not surprising that Panels A and B of Figure 5 show no statistically detectable effects on aggregate unemployment or inactivity shares. Although point estimates are generally of the expected sign, they are small and imprecise, indicating that platform entry does not materially alter labor-market conditions at the population level.

This absence of aggregate effects masks substantial heterogeneity. Panels C and D focus on men, who account for the vast majority of rider take-up. Here, platform entry is followed by clear declines along both margins: male unemployment falls by about 1.5% on average in the post-entry period, while male inactivity declines by roughly 2%. These effects emerge gradually after entry, mirroring the sustained increase in rider registrations documented in Section 6.1, and point to genuine labor-market activation rather than short-run reallocation.

The strongest effect is associated with male migrants, shown in Panels E and F of Figure 5. Though unemployment among male migrants declines (by a magnitude similar to that observed for men overall, but estimated with greater uncertainty), the dominant adjustment occurs along the inactivity margin: inactivity falls by approximately 9% following platform entry. This asymmetry is informative. It indicates that platform jobs draw migrant men primarily from outside the formal labor market altogether rather than from registered unemployment. We also expect an age gradient in the response of male migrants, with effects declining with age. Consistent with this expectation, inactivity falls by about 14% among the youngest group (15–24), by about 7% among those aged 25–54, and shows no detectable change for ages 55–65 (see Appendix Figure A8). This pattern closely mirrors the descriptive evidence in Section 4.2: riders are disproportionately young men of migrant origin, often residing in disadvantaged areas. Table 2 shows that the majority enter delivery work from inactivity rather than from prior employment. Because many migrant men are inactive, they are not eligible for unemployment benefits, making rider jobs their first experience of legal employment.

By contrast, we do not find comparable labor-market effects for women (see Appendix Figure A9). Event-study estimates for unemployment and inactivity among women and migrant women are small and statistically indistinguishable from zero, consistent with the near absence of female rider take-up documented earlier. We find weak and imprecise evidence of a slight increase in female inactivity, but this pattern is not robust across specifications and does not persist across post-entry years. Importantly, these null effects for women also serve as a placebo test. If platforms entered areas experiencing broader improvements in local economic conditions, we would expect to observe parallel declines in unemployment or inactivity among women as well. The absence of such effects strengthens

Figure 5: Impact of Platform Entry on Labor-Market Outcomes



Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Baselines are from 2014. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown. Jurisdictions excluded due to zero values in the outcome variable: 1 (Panel E) and 3 (Panel F).

the interpretation that the labor-market responses documented above are driven by access to platform jobs, rather than by coincident local economic trends.

One potential concern raised by the weak increase in female inactivity is whether platform entry displaces women from other low-skill service jobs. We therefore examine employment responses in restaurants and supermarkets, two sectors that employ similar worker profiles and are closely tied to local consumption demand. Appendix Figure A10 shows that employment in these sectors does not exhibit statistically significant declines following platform entry, although point estimates in some specifications are negative and confidence intervals approach zero. At the same time, the number of establishments per capita slightly increases. This pattern is consistent with, at most, limited substitution within low-skill service employment, combined with mild expansion in local commercial activity. Importantly, even if some reallocation across low-skill jobs occurs, it does not alter our main findings: female take-up of delivery work remains minimal, and the labor-market effects of platform entry are concentrated among men—especially migrant men–who predominantly enter from inactivity rather than from other jobs.

Overall, the labor-market evidence indicates that platform entry primarily operates through activation at the extensive margin among men, and especially migrant men, who would otherwise remain inactive. The absence of aggregate employment effects reflects the modest scale of platform jobs relative to local labor markets, not the absence of meaningful adjustment for the populations most affected by platform access. These patterns directly motivate the analysis of crime outcomes that follows.

6.3 Crime Outcomes

We now investigate how the entry of food-delivery platforms affects criminal activity. Figure 6 presents event-study estimates for a range of crime categories. Pre-entry coefficients are relatively flat across panels, especially for the offense categories that exhibit the largest post-entry declines, and do not display systematic differential trends prior to platform entry. Following entry, we observe clear and persistent reductions concentrated in offense types that are disproportionately committed by young men with weak attachment to the labor market—the same groups that account for the bulk of rider take-up (Sections 4.2 and 6.2).

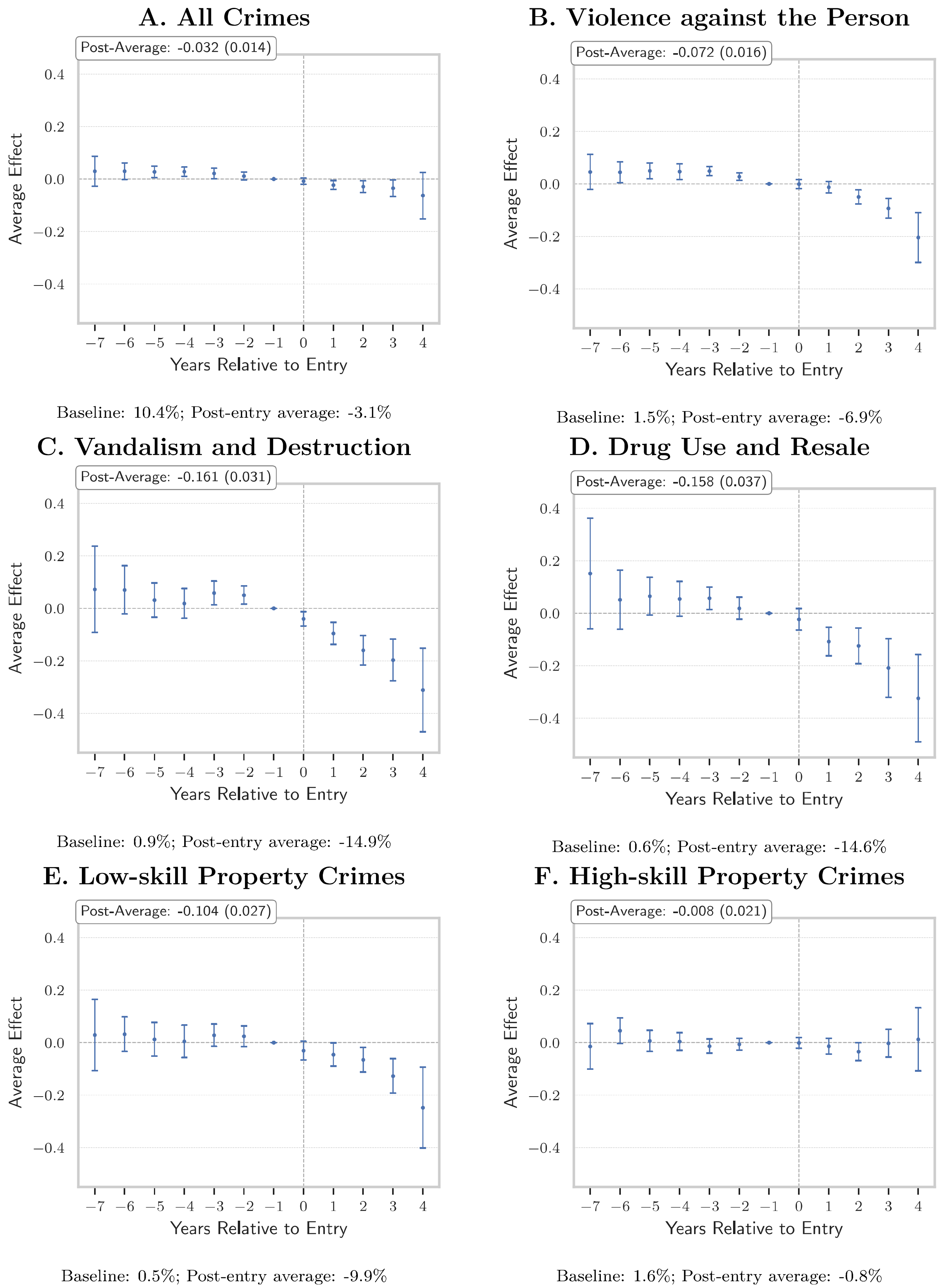
Panel A of Figure 6 shows that overall recorded crime declines by about 3.1% after platform entry. The decline is more pronounced for violence against the person, a major subcategory of recorded offenses (–6.9%; Panel B), consistent with both income-substitution and incapacitation mechanisms: access to regular legal earnings and reallocation of time away from idle or high-risk activities reduces exposure to situations in which interpersonal conflict is most likely to arise.

The largest effects are observed for vandalism and destruction of property (–14.9%; Panel C) and for drug-related offenses (-14.6%; Panel D). The sharp decline in vandalism is particularly consistent with an incapacitation channel, as these offenses are disproportionately committed by adolescents and young adults and tend to occur during periods of unsupervised leisure time. By contrast, the reduction in drug offenses aligns more closely with an income-substitution mechanism: platform work provides a legal, immediately accessible alternative to low-level drug dealing for individuals facing barriers to formal employment. This interpretation echoes the qualitative motivation discussed in the introduction, where riders describe delivery work as preferable to "more nefarious ways of making money" (New York Times, June 16, 2019).

Distinguishing property crimes by skill intensity further clarifies the mechanisms. Low-skill property crimes such as shoplifting and street robbery fall by about 10% following platform entry (Panel E). These offenses require little planning or specialization and are most prevalent among individuals without stable income. In contrast, we find no detectable effect on higher-skill property crimes such as burglary and vehicle theft (Panel F), which typically involve experience, networks, and higher fixed costs. This sharp contrast indicates that platform access affects marginal, entry-level criminal activity rather than professionalized crime.

Overall, the pattern of results closely corresponds with the mechanisms outlined in our conceptual framework (Section 2). Platform work increases the relative attractiveness of legal income for individuals facing labor-market exclusion (*economic deterrence*) and reduces unstructured time during evenings and weekends when opportunistic crime is most likely (*self-incapacitation*). The fact that crime reductions are concentrated in low-skill, short-horizon offenses but not in more organized or skill-intensive crimes provides strong evidence that platform entry shifts behavior among individuals at the margin between informal, illicit, and legal income sources.

Figure 6: Impact of Platform Entry on Crime



Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Baselines are from 2014. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown. Jurisdictions excluded due to zero values in the outcome variable: 1 (Panel E).

6.3.1 Crime Effects in Light of Rider Take-Up

To assess whether the estimated crime effects are economically meaningful, we relate the magnitude of rider take-up to the implied reductions in criminal activity. Table 3 reports post-entry average effects and translates the log estimates into absolute changes using baseline crime rates per 10,000 residents. Platform entry increases rider registrations by about 32 per 10,000 working-age residents, and by roughly 62 per 10,000 among men. While this expansion is modest relative to the size of local labor markets, it is concentrated in groups with higher exposure to illegal income opportunities and police contact.

As documented in Section 4.2, new riders are predominantly men in their early twenties, frequently inactive or unemployed prior to entry, and disproportionately of migrant origin. Because French administrative crime data do not permit the construction of statistics by ethnicity or ancestry, we rely on national security surveys to characterize differential exposure to policing and criminal justice contact across groups. These surveys report that identity check rates in France are roughly four times higher for young men perceived as North African or Black than for other groups, and in-depth security screenings are up to twelve times higher.[26] These statistics provide an informative proxy for differential exposure to police contact and arrest. The same groups exhibit the largest take-up of platform work following entry.

Table 3 shows that the largest crime reductions occur for drug-related activity, low-skill property crime, and vandalism—offenses that are disproportionately concentrated among young men with weak attachment to formal employment. Using police records for 2019, INSEE reports that offending rates peak sharply among individuals aged 15–29 and decline rapidly thereafter (INSEE, 2021). These offenses require little capital or specialization and primarily serve short-run income needs. In this context, a shift of several dozen young men per 10,000 residents into delivery work—which can offer immediate employment and predictable daily earnings—is sufficient to plausibly generate the observed reductions in these crime categories.

Seen through this lens, the magnitudes in Table 3 are consistent with a reallocation of high-risk individuals from illicit to legal income-generating activities following the roll-out of food-delivery platforms. The effects we document therefore do not reflect broad,

[26] 2025 report of the Defender of Rights (*Défenseur des droits*) on Police/citizen relations: identity checks and filing complaints.

Table 3: Translating Estimated Effects into Absolute Crime Reductions

	Post	Baseline	Absolute Effect
	Average	per 10,000 population	
Riders	**+32.3*****	—	**+32.3**
Male riders	**+62.3*****	—	**+62.3**
Male riders not born in France	**+105.0*****	—	**+105.0**
All crimes (Log)	**-3.1%****	1038	**-32.2**
Violence against the person (Log)	**-6.9%*****	153	**-10.6**
Vandalism/destruction of property (Log)	**-14.9%*****	90	**-13.4**
Drug use and resale (Log)	**-14.6%*****	59	**-9.6**
Low-skill property crimes (Log)	**-9.9%*****	51	**-5.0**

Notes: Baselines represent average crime rates per 10,000 population aged 15-54 in 2014. Absolute effects are computed by multiplying the post-average effect by the baseline values. Rider estimates are extracted from regressions presented in Figure 4: (A) all riders; (B) male riders, and (C) male riders not born in France. Crime estimates correspond to Figure 6: (A) all crimes; (B) violence against the person; (C) vandalism and destruction of property; (D) Drug use and resale; (E) low-skill property crimes. Significance: $^{*}p < 0.1$;$^{**}p < 0.05$ and $^{***}p < 0.01$.

economy-wide changes in criminal behavior, but targeted responses among populations at the margin between informal and illegal work, for whom access to low-barrier gig jobs meaningfully alters the set of feasible earning opportunities.

7 Mechanism and Robustness

7.1 Age-Based Eligibility Test

A key implication of the mechanisms outlined in Section 2 is that crime reductions should be concentrated among individuals who become newly eligible to take up platform work. Food-delivery platforms require riders to be at least 18 years old to register as micro-entrepreneurs. This institutional feature provides a sharp test of the mechanism: if platform entry affects crime through access to legal earning opportunities and changes in time allocation, reductions should occur among offenders aged 18 and above, with no comparable response among minors.

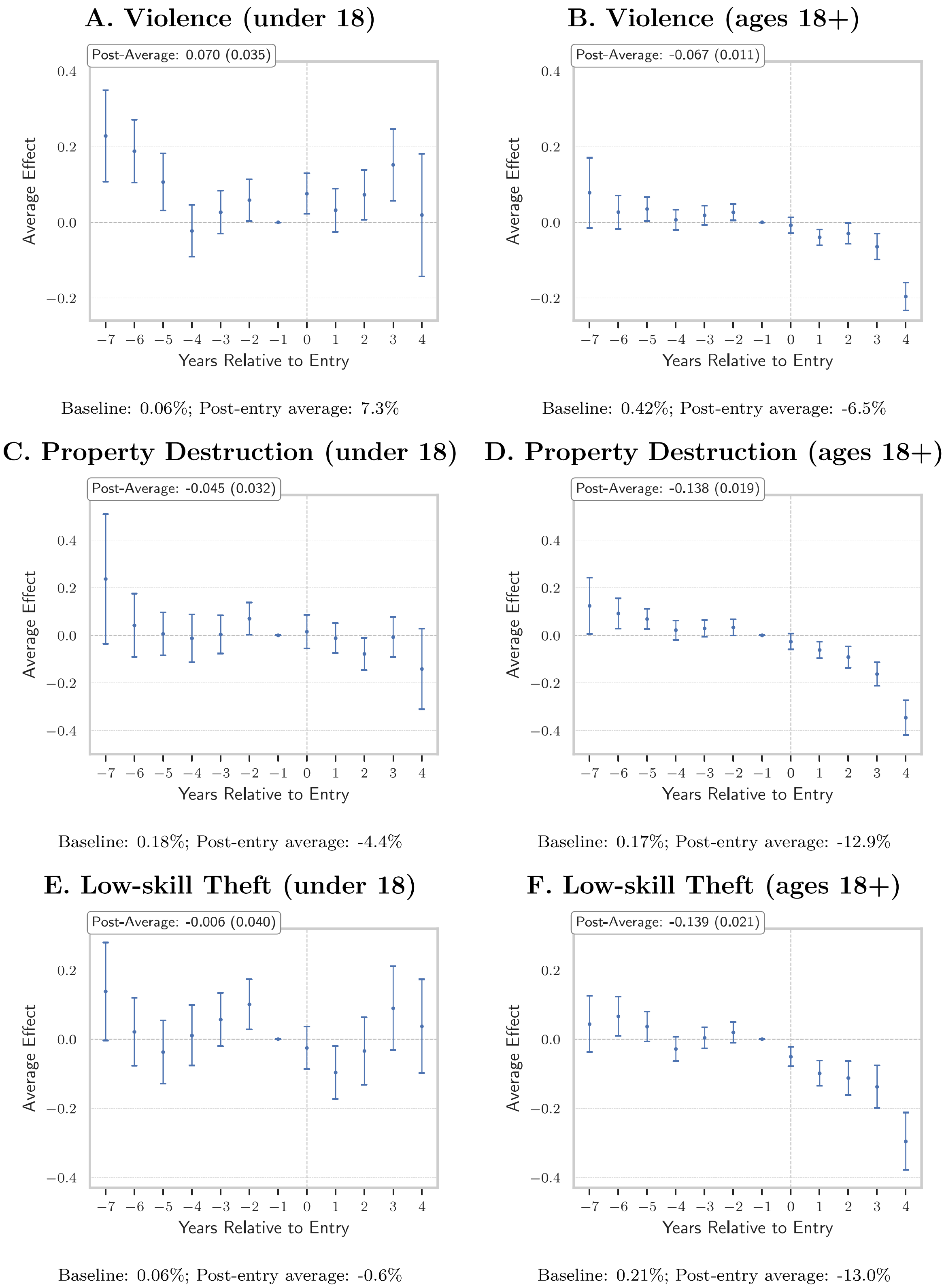
To implement this test, we use court records that report offenses by age of the perpetrator. We focus on three crime categories, violence against the person, destruction of property, and low-skill theft, that satisfy two criteria. First, these categories correspond to the police-reported offenses analyzed in Section 6.3. Second, they are reliably observed in court data during our sample period. By contrast, drug-related offenses are less suitable. Many drug offenses never reach court proceedings, as alternative sanctions were increasingly used during our period of study to reduce court congestion, such as on-the-spot fines for consumption. Furthermore, drug offenses present classification challenges because police and court categories do not align well. The distinction between supply- and demand-side activity is often ambiguous, for instance, when an arrested seller claims that the drugs were for personal use. As a result, the same conduct may be coded differently in police records and later reclassified in court.

In contrast, the three selected categories face fewer classification issues and typically involve offenses serious enough to be prosecuted in criminal court. Still, each category has limitations, with the exception of destruction of property, which provides the closest match between police and court records. First, violence against the person, including rapes and serious assaults, does not perfectly match police data, as some of the most serious offenses are judged in assize courts, which are not covered in our data. Second, low-skill theft faces the reverse issue, as offenders of shoplifting and pickpocketing are rarely caught, leading to underestimation.

Figure 7 presents event-study estimates separately for individuals under 18 and those aged 18 to 39. Across all three offense categories, crime among minors remains flat following platform entry, with no detectable post-entry trend. In contrast, offenses committed by adults decline sharply after entry. Violence falls by about 6.5%, while destruction of property and low-skill theft decline by nearly 13%. Pre-entry estimates are flat for both age groups, consistent with parallel trends prior to platform entry.

The age contrast is particularly informative in light of the underlying age distribution of these crimes. As documented in Appendix R and summarized in the figure notes, destruction of property and low-skill theft are heavily concentrated among young individuals, with substantial mass below age 18. Violence against the person is less sharply age-concentrated and is estimated with greater imprecision in the court data, but its post-entry pattern is nonetheless consistent with a labor-supply–based mechanism in which access to legal work raises opportunity costs and reduces idle time. The fact that reductions are concentrated in offense categories that are most prevalent among young adults—and that plausibly respond to changes in short-run income opportunities and time use—reinforces the interpretation that platform entry affects behavior at the margin of labor-market

Figure 7: Crime Effects by Eligibility for Gig Work (Under 18 vs. 18+)



Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Logged annual outcomes at the jurisdiction level for minors (under 18) and adults (18-39). The vertical dashed line marks event time 0. Baselines are from 2014. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown. Age distributions are reported in Appendix R.

eligibility.

Explanations based on changes in policing intensity, reporting practices, or broader area-level dynamics would not predict a discontinuity precisely at the legal working-age cutoff. Nor would such explanations generate stable crime patterns among minors alongside pronounced declines among adults. Instead, the evidence is consistent with a mechanism in which platform entry expands access to flexible, low-barrier legal work for newly eligible individuals, shifting both income opportunities and the allocation of time away from activities associated with opportunistic offending.

Finally, while our labor-market analysis shows no meaningful effects of platform entry for women, we are unable to conduct an analogous age-based test by gender using court data. Women account for less than 10 percent of court-recorded offenses in our sample, yielding cell sizes that are too small to support reliable event-study estimates at the police-jurisdiction level. The age-based eligibility test therefore provides the cleanest and most informative quasi-experimental evidence on the mechanism linking platform entry to crime.

7.2 Platform Entry Beyond Major Urban Districts

A natural concern is that the estimated effects are driven by France's largest urban centers, where food-delivery platforms first entered and where labor-market conditions, policing intensity, and crime dynamics may differ from those in smaller jurisdictions. If platform rollout coincided with broader economic or institutional changes specific to these metropolitan cores, our estimates could reflect such confounding trends rather than the expansion of access to gig work.

To address this concern, we re-estimate our baseline specifications after excluding the police districts corresponding to the urban cores of Paris, Marseille, and Lyon, the three most populous cities in France. Together, these districts account for nearly three million working-age residents. Crucially, we retain suburban police jurisdictions located within 15 km of these cities. Although delivery demand and restaurant coverage are concentrated in city centers, many riders reside in surrounding suburbs and commute into the urban core to work. As shown in the spatial rider maps in Appendix K, the residential distribution of riders is more spatially dispersed than the geography of platform restaurant operations. These suburban jurisdictions are therefore meaningfully exposed to platform entry: local residents gain access to platform-based employment opportunities even when no deliveries take place within their own district at the time of entry. This feature allows us to isolate the labor-supply channel from confounding changes in local commercial activity, foot traffic, or city-center policing.

Re-estimating our models on this restricted sample yields results nearly identical to the baseline. Platform entry continues to generate a strong increase in rider registrations, concentrated among young men and individuals of migrant origin, and comparable declines in vandalism, drug offenses, and low-skill property crime. Appendix Section O reports the estimates.

This robustness exercise shows that our main results are not driven by dynamics specific to major metropolitan centers, nor by changes in city-center delivery markets or consumption patterns. Instead, the evidence supports a mechanism operating where riders live: platform entry expands access to flexible, low-barrier legal work in residential areas, and this expansion underlies the observed reductions in crime.

7.3 Could Changes in Movement or Detection Explain Crime Reductions?

An alternative interpretation of the crime reductions documented above is that they stem from changes in opportunities for offending or in the visibility of offenses, rather than from changes in underlying criminal behavior. In particular, platform entry could shift public activity if consumers stay home and order meals instead of going out, and it could also affect detection and reporting. We therefore examine outcomes that would respond mechanically to such channels.

A first possibility is that platform rollout changes public activity, for example if consumers stay home and order meals instead of going out. Such a shift could mechanically affect crime by changing the supply of potential victims rather than offenders' behavior. Two patterns argue against this interpretation. First, burglary rates remain flat following platform entry (see Appendix Figure A18a). If more people were staying at home, burglaries should fall because dwellings would be less often unattended. The absence of any such decline indicates that platform entry does not generate a large, purely mechanical "stay-at-home" effect.

Moreover, we observe marked declines in shoplifting and other low-skill theft offenses (see Appendix Figure A18b). Unlike street crime, shoplifting does not depend on the presence of victims in public space, since retail locations remain open and accessible. Declines in shoplifting therefore cannot be explained by changes in public movement or victim exposure and instead point to changes in offenders' behavior.

A related concern is selective residential sorting: potential riders——particularly young migrant men——might move toward jurisdictions where gig-work becomes available, mechanically affecting local outcomes. Appendix Figure A18c addresses this concern by plotting an event study of the log population of male migrants aged 15-54. Population levels are flat before and after entry, with no detectable post-entry response, ruling out selective in-migration as a driver of our results.

A second possibility is that declines in drug-related offenses reflect changes in how drugs are distributed rather than changes in the offenses themselves. Journalistic accounts suggest that app-based ordering and delivery of cannabis expanded during the late 2010s and the COVID-19 period, potentially reducing the visibility of transactions and lowering recorded offenses even if the underlying activity remained unchanged. Although this interpretation cannot be ruled out entirely, several features of the data make it unlikely to explain our findings. The declines in drug offenses appear immediately following platform entry, whereas the diffusion of app-based drug delivery is documented to lag by several years. Moreover, we observe contemporaneous reductions in vandalism, low-skill theft, and violence—offenses that are not plausibly affected by changes in drug distribution technology. The alignment of effects across these categories points to a common behavioral mechanism rather than to changes in detection specific to drug markets.

The evidence suggests that the uncovered crime reductions are unlikely to be driven by changes in public movement or by shifts in the visibility of particular offenses. Instead, the consistent declines across multiple low-skill, income-generating crimes, those most concentrated among young men with weak labor-market attachment, support the interpretation developed above: platform entry expands access to legal earning opportunities at the margin, and this expansion leads to meaningful reductions in criminal activity.

8 Conclusion

This paper examines how the diffusion of food-delivery platforms shapes local labor markets and crime in France. Using staggered platform entry and linked administrative data, we show that rollout increases participation in gig-work, particularly among young men from immigrant-origin backgrounds with weak prior attachment to wage employment. In the years following entry, crime rates decline, especially for offenses that are most common among this demographic and require little skill or capital, such as drug offenses and low-skill property crime.

The labor market and crime effects closely align. Platform entry expands access to legal earning opportunities for groups facing structural barriers to formal employment. The resulting activation into work is visible in declines in inactivity and unemployment among male migrants, but does not meaningfully shift aggregate employment or unemployment indicators. Correspondingly, crime reductions emerge in offense types where offenders are most likely to substitute toward gig-income. We find no evidence of displacement from traditional low-skill sectors: neither restaurant nor supermarket employment declines, and establishment counts in these sectors slightly increase, suggesting mild commercial expansion rather than job crowd-out.

Robustness analyses reinforce the interpretation that the crime drop is driven by access to gig-work rather than unrelated urban changes. Excluding the three largest cities—while retaining their surrounding commuter suburbs where riders live—yields effect sizes that are essentially unchanged. Crime declines are also not driven by shifts in public activity or policing intensity: burglaries remain flat, bar activity is stable, and shoplifting (which does not depend on victim presence) declines markedly. Although some displacement of drug transactions to online delivery markets cannot be entirely ruled out, the immediate timing of the crime decline, the age discontinuity at the legal entry threshold, and the concentration of effects in offense types associated with informal subsistence income collectively support a labor-substitution mechanism.

The evidence points to a specific role played by gig-work in contexts of labor market exclusion. Platforms lower the barriers to legal employment by reducing screening frictions and credential requirements. For individuals at the margin of legal and illegal income opportunities, the availability of flexible, low-barrier work shifts behavior away from criminal activity. In this sense, gig-jobs function as a short-run outside option that reduces involvement in entry-level crime. However, these short-run benefits should not be interpreted as evidence of upward labor-market mobility. Recent work by Adermon and Hensvik (2022) shows that while gig experience improves employment prospects relative to unemployment, it yields far weaker gains than traditional work experience and offers little advancement for workers with immigrant-origin names. Gig-jobs may therefore be preferable to no job, but they are unlikely to resolve deeper structural barriers in the labor market.

This pattern suggests a broader implication: improving access to legal income opportunities for disadvantaged groups can meaningfully reduce crime, even when those opportunities are temporary, flexible, and low-paid. The longer-run challenge is whether such jobs can be complemented with pathways that build skills and translate into stable employment. Recent evidence for refugees points to limited longer-run gains (Degenhardt and Nimczik, 2025), underscoring the need for further research on how short-run access to gig work can be paired with durable integration policies.

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Appendix

A A Simple Conceptual Framework

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

Delivery Platforms — There are $z = \{1, \ldots, Z\}$ economic zones, each representing a distinct location of varying size. Delivery platforms evaluate these locations for potential entry based on the availability of restaurants (supply), consumers (demand), and riders.

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

Group g workers encounter significant barriers to employment in the legal sector (see Appendix B). Let U_L denote the expected utility from low-skilled legal work:

$$U_L = \omega_L - f.$$

where ω_L is the minimum wage, and f summarizes labor-market frictions as a disutility and cost (e.g., hiring-stage discrimination, documentation requirements such as a CV, and search time).

Confronted with barriers to employment, g workers may turn to low-skill and income-generating crime, such as street-level drug dealing and shoplifting. This substitution may happen despite the greater regularity, safety, and benefits of legal jobs. Let U_I denote the expected utility from illegal work:

$$U_I = \omega_I - pC - h,$$

where ω_I is a random variable, with cumulative distribution F, representing the illegal wage derived from low-skill and income-generating crime, p is the probability of getting caught, C is the associated cost (monetary or otherwise, e.g., incarceration), and $h \geq 0$ denotes the disutility of committing offenses during peak-crime hours (evenings/weekends, which overlap with peak delivery hours).[27]

An individual chooses the illegal job if its expected utility exceeds that of the low-skilled job; that is,

$$\omega_I > \omega_L - f + pC + h.$$

Let $\tau \equiv \omega_L - f + pC + \phi(h)$ denote the threshold. The probability of choosing illegal work is

$$P_I = \mathbb{P}\Big(\omega_I > \tau = 1 - F(\tau)\Big),$$

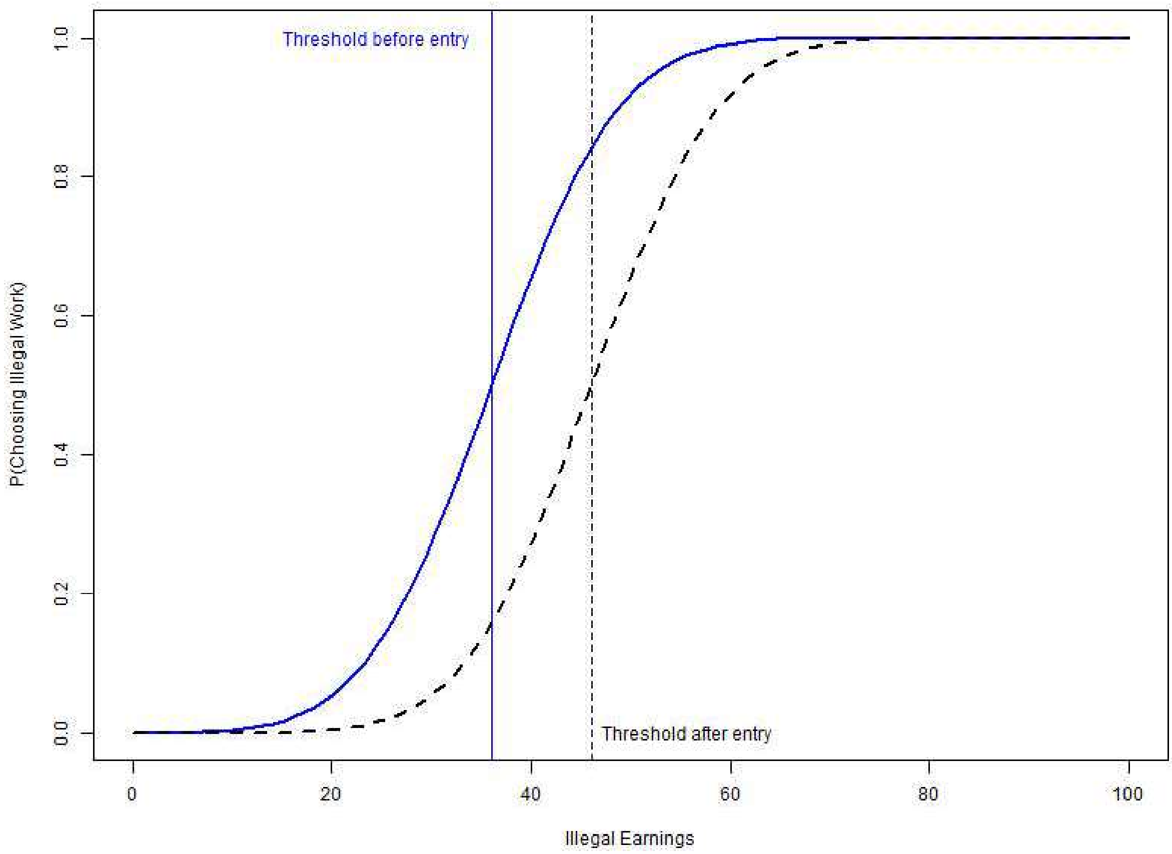
that is, the likelihood that potential illegal earnings exceed the net payoff from legal work.

Platform Entry — Entry and availability of a delivery platform in location z generates two effects: (1) economic deterrence by lowering barriers to employment (reducing f), and

[27]For the sake of illustrating the partial effect of platform entry, we assume simple linear utility functions. For instance, the effort/disutility from work is assumed to be equal across activities, and the offender retains ω_I even if caught.

(2) self-incapacitation effect by occupying peak-crime hours with delivery work (raising h). Both effects increase the threshold τ reducing P_I. As a consequence, in Figure A1, the threshold shifts right: illegal work must offer a higher wage to be preferred to legal work. This visual representation underscores the potential benefits of policies aimed at enhancing legal job opportunities for at-risk populations.

Figure A1: Conceptual Model – Shift in Crime Threshold



Notes: The solid blue curve represents the cumulative distribution of illegal earnings before the entry (or availability) of delivery platforms in a location; the dashed black curve represents the distribution after the entry. The vertical lines indicate the thresholds before (solid blue) and after (dashed black) the entry of platforms.

The conceptual framework underpins our empirical difference-in-differences approach, which compares pre- and post-platform entry in z to a control location z', where the platform has not entered. We expect not only more riders in z but also a decrease in crime. Let G be the size of group g, then $G_I = pG[1 - F(\tau)]$ is the number of individuals from g engaged in illegal activities. Because $\partial\tau/\partial f = -1$, we have $\partial G_I/\partial f > 0$: reducing barriers to employment f (via platform entry) raises τ and lowers G_I. Likewise, $\partial G_I/\partial h < 0$: self-incapacitation reduces the number of individuals from g engaged in illegal activities.

B French Labor Market Features

Table A1: Labor Market Outcomes: first- and second-generation migrants, 2022 (in %)

	Inactivity Rate	**Employment Rate**	**Unemployment Rate**
First-generation immigrant[a]	30.0	61.8	11.7
Second-generation immigrant[b]	32.2	60.5	10.8
Non-immigrant[c]	25.1	70.2	6.3
Total population	26.5	68.1	7.3

Notes: All rates are computed for individuals aged 15–64 living in France (excluding Mayotte). Inactive rate = inactive (neither employed nor unemployed) ÷ total population. Employment rate = employed ÷ total population. Unemployment rate = unemployed ÷ labor force (employed + unemployed). In 2022, among first-generation immigrants aged 15 to 64, 30.0% were inactive and 61.8% were employed. Among those active in the labor force, 11.7% were unemployed.

[a]First-generation immigrant: born abroad and residing in France. Individuals continue to be considered immigrants even if they acquire French nationality. [b]Second-generation immigrant: native-born with at least one foreign-born parent. [c]Non-immigrant: native-born with two native-born parents.

Source: INSEE, Labor Force Survey (accessed August 2024). Note that the INSEE website provides only the latest available year at any given time.

Table A2: Inactivity, employment, and unemployment rates of immigrants by geographic origin, 2022 (in %)

	First-Generation[a]			**Second-Generation**[b]		
	Inactivity Rate	Emp. Rate	Unemp. Rate	Inactivity Rate	Emp. Rate	Unemp. Rate
Africa	31.3	59.3	13.7	38.0	52.6	15.2
Maghreb*	34.4	56.6	13.7	37.0	53.8	14.5
Other	26.2	63.7	13.7	41.0	48.8	17.3
Asia	31.3	60.8	11.5	37.6	55.3	11.4
Turkey, Middle East	31.8	58.3	14.5	39.4	51.4	15.2
Other	30.9	62.7	9.1	35.8	59.2	7.8
Southeast Asia	24.2	70.0	7.7	27.2	66.6	8.5
Americas, Oceania	31.8	59.4	12.8	45.3	47.2	13.7
Europe	26.3	67.7	8.1	22.5	72.5	6.3
Southern Europe†	25.2	70.7	5.6	19.2	76.2	5.7
Other EU–27	23.4	69.5	9.3	32.0	62.1	8.7
Other	30.9	61.5	10.9	32.7	61.9	8.0
Non-immigrant[c]	25.1	70.2	6.3	25.1	70.2	6.3

Notes: All rates are computed for individuals aged 15–64 living in France (excluding Mayotte). Inactive rate = inactive (neither employed nor unemployed) ÷ total population. Emp. (Employment) rate = employed ÷ total population. (Unemp.) Unemployment rate = unemployed ÷ labor force (employed + unemployed). In 2022, among first-generation immigrants from Africa aged 15 to 64, 31.3% were inactive and 59.3% were employed. Among those active in the labor force, 13.7% were unemployed.

The country of origin is the country of birth of the immigrant parent if there is only one. When both parents are immigrants, the father's origin is used by convention.

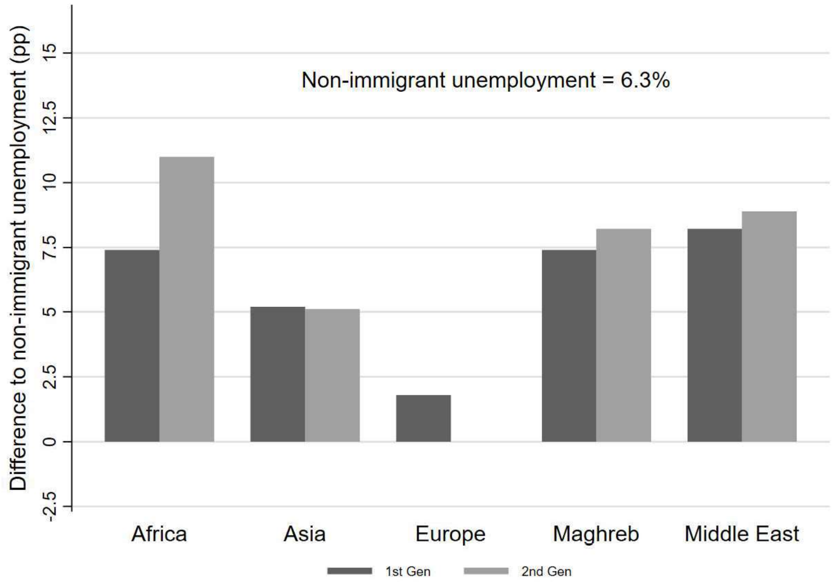
[a]First-generation immigrants: born abroad and residing in France. Individuals continue to be considered immigrants even if they acquire French nationality. [b]Second-generation immigrants: native-born with at least one foreign-born parent. [c]Non-immigrant: native-born with two native-born parents.

*Maghreb: Algeria, Morocco, Tunisia. †Southern Europe: Portugal, Spain, Italy. "Other" represents other countries within each region.

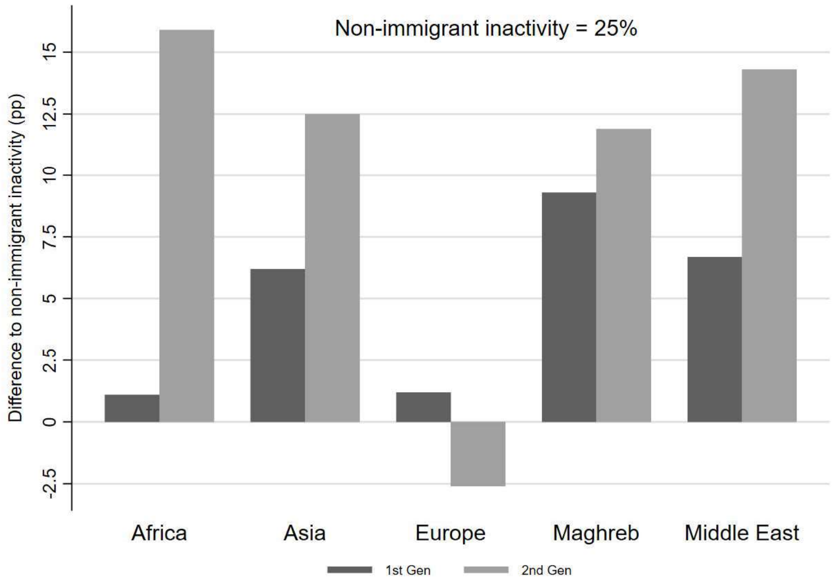
Source: INSEE, Labor Force Survey (accessed August 2024). Note that the INSEE website provides only the latest available year at any given time.

Figure A2: Unemployment and Inactivity by Origin, 2022

Unemployment



Inactivity



Notes: All rates are computed for individuals aged 15–64 living in France (excluding Mayotte), and differences are measured relative to non-immigrants (native-born with two native-born parents). See Appendix Tables A1 and A2 for raw numbers. Inactive rate = inactive (neither employed nor unemployed) ÷ total population. Unemployment rate = unemployed ÷ labor force (employed + unemployed). The country of origin is the country of birth of the immigrant parent if there is only one. When both parents are immigrants, the father's origin is used by convention. "1st Generation": born abroad and residing in France. "2nd Generation": native-born with at least one foreign-born parent. Origin groups: Africa (excluding Maghreb); Asia; Europe (excluding France); Maghreb (Algeria, Morocco, Tunisia); Middle East (including Turkey).
Source: INSEE, Labor Force Survey (accessed August 2024). Note that the INSEE website provides only the latest available year at any given time.

C Survey Evidence on Food Riders in Paris, 2016-2019

This appendix is based on three rider surveys conducted in Eastern Paris (see Dablanc et al., 2019, 2020). The first surveyed 96 riders (Oct–Dec 2016); the second, 107 riders (Jan–Mar 2018); the third, 300 riders (Dec 2019–Jan 2020).

Table A3: Summary of Three Rider Surveys in Eastern Paris

	2016 (1)	2018 (2)	2019 (3)
Demographics (%)			
Women	2	5	2
Age < 35	92	94	88
No diploma or middle school education	30	33	66$^{(a)}$
Bicycle as main mode of delivery	78	73	62
Weekly hours distribution (%)			
$<$ 10 hours	53	56	30
10–20 hours	36	40	60
$>$ 20 hours	6	11	10
Main reasons for being a rider (%)			
Only job I could find	–	17	$^{(b)}$
Wanted high autonomy	–	40	–
Self-declared nationality (%)			
French	–	–	14
Foreigner	–	–	86
Observations	96	107	300

Notes: Percentages are as reported in the original surveys. In 2019: (a) among the 215 full-time riders, 50% report no diploma; (b) 43% of riders answered "yes" to the question, "I can't find another job."
Source: Three rider surveys conducted in Eastern Paris (Dablanc et al., 2019, 2020). Column (1): 96 riders (Oct–Dec 2016); Column (2): 107 riders (Jan–Mar 2018); Column (3): 300 riders (Dec 2019–Jan 2020).

The survey evidence in Appendix Table A3 points to a clear rider profile: overwhelmingly male (2–5% women), very young (88–94% under 35), and largely first-generation migrants (86% foreign nationals in 2019). Education is low, about one-third report no diploma or only middle-school education in 2016–2018, rising to two-thirds in 2019. Bicycles are the main mode (62–78%). Most work fewer than 20 hours/week, citing both autonomy (40% in 2018) and lack of alternatives (17% in 2018; 43% in 2019 said they "can't find another job").

D Rider's Origins

Appendix B documents that first- and second-generation immigrants experience higher rates of inactivity and unemployment than natives, with larger disparities among non-

European groups, such as African migrants. These statistics are produced by INSEE, an institution authorized by French law to compile origin-based indicators using official sources (e.g., census and dedicated surveys). By contrast, the collection and dissemination of ethnic statistics in France are strictly regulated, which limits the amount of individual-level information on migration background in the datasets we analyze. Due to these legal restrictions, we take an alternative approach to evaluating the origins of delivery workers and the potential labor-market discrimination they may have experienced before entering delivery work.

Compliance with French regulations requires that riders remain non-identifiable, even when their names are publicly available. The *SIRENE* dataset lists 153,322 unique riders between 2012 and 2019, identified under NAF code 53.20Z. From this list, We exclude 37,612 observations without a recorded first name. Then, to preserve anonymity, we drop 12,929 unique first names that could enable identification.[28]

This created dataset is non-identifiable, as it contains exclusively non-unique first names with no other information. We then employ the paid version of Claude, a series of large language models (LLMs), to classify the list of first names into four geographic categories: Arabic, Asian, European, and Sub-Saharan.[29] We want to stress several points. First, we never merged this name-geographical information back with the original Sirene database. Second, this name-based approach reflects geographic origin associated with naming conventions rather than genetic ancestry. This methodology has inherent limitations: it may oversimplify diversity, miss regional specificity, and fail to capture the complex geographic landscape within and across groups. However, it allows us to obtain an indication of the number of riders likely to face discrimination in the labor market.

E Uber Eats and Deliveroo Rollout in France

Uber Eats and Deliveroo are the two largest delivery platforms in France, and thus the most likely to affect local labor markets and crime. Uber Eats launched in 2014 and entered France in 2015. Deliveroo launched in 2013 in the United Kingdom and was rolled out in France in 2015.[30]

Entry dates for Uber Eats and Deliveroo were assembled from multiple sources. First, we collected launch dates from national and regional media. Second, for Uber Eats, we retrieved city-specific entry dates from archived versions of the Uber Eats website using the Wayback Machine.[31] Third, we cross-checked and supplemented these data with the *Collectif Data + Local*.[32] Finally, Uber provided information on its "reference areas," allowing us to verify coverage of all Uber Eats areas and entries back to 2015. Additionally, we check whether the increase in the number of registered riders by city aligns with the first recorded platform entry date (see Figure 1).

[28] For unique compound first names, we only retain the first component, provided it is not unique.

[29] This classification available upon request was done on September 27, 2025.

[30] In July 2015, Deliveroo reported partnerships with 250 restaurants in France (see https://www.lesechos.fr/2015/07, last accessed October 2025.)

[31] Deliveroo does not display entry dates on its website; therefore, we relied on national and regional press and Twitter archives.

[32] A consortium of journalists covering major local media in France; see Collectif Data + Local.

F Self-employment Registration in France

In France, riders should register as self-employed. This micro-entrepreneur status, established in 2009, was designed to simplify the creation and management of small individual businesses, particularly those with low turnover.[33] The micro-entrepreneur status is particularly attractive for individuals seeking flexible work, such as riders (see Appendix C). Micro-entrepreneur registration requires minimal administrative formalities without any significant upfront costs. Riders are classified with the activity NACE code 53.20Z ("Other postal and courier activities").[34]

The micro-entrepreneur registration can be completed either in person, at the *Centre de formalités des entreprises* (CFE), or online. Riders provide the following information:

- Identity: Full name, date and place of birth, nationality, and address.
- Nature of activity: "Bike delivery" or "transportation of goods/people using a two-wheeled vehicle." The activity falls under "Industrial and Commercial Services" within the micro-entrepreneur regime.
- Start date: Desired start date of the activity.
- Siret number: A 14-digit unique identifier (*Système d'Identification du Répertoire des Établissements*) issued upon registration; it serves as official proof of registration and allows riders to operate legally and issue invoices.
- Bank account: before 2019, riders could use a personal bank account for professional transactions; since 2019, a dedicated business account is required if the annual turnover exceeds €10,000 for two consecutive calendar years.[35]
- Honor statement: a simple *déclaration sur l'honneur de non-condamnation* attesting the absence of disqualifying criminal or commercial convictions.

Once registered as a micro-entrepreneur, the rider must self-declare turnover to URSSAF (the French social welfare collection agency).[36] Before 2018, the annual turnover threshold for service activities was €33,100. It doubled in 2018 to €66,200. Beyond these thresholds, the rider exits the simplified micro-entrepreneur scheme and moves to a more complex tax and social-security regime. Within the simplified scheme, riders may choose between the *versement libératoire de l'impôt sur le revenu*, paying income tax as a fixed percentage of turnover (1.7%), and the default micro-fiscal regime, which taxes 50% of turnover at the progressive household rate. The same social contributions apply in both cases. Under the simplified scheme, riders are affiliated with the *Régime social des indépendants*, providing basic coverage (health, retirement).[37]

[33] https://www.insee.fr/en/metadonnees/definition/c2066, last accessed October 2025.

[34] https://www.insee.fr/en/metadonnees/nafr2/sousClasse/53.20z, last accessed October 2025

[35] www.urssaf.fr, last accessed November 2025. To help riders open a bank account and management administrative procedures, Deliveroo created in 2018 a partnership with the online banking service Shine. Source: lesechos.fr, last accessed November 2025.

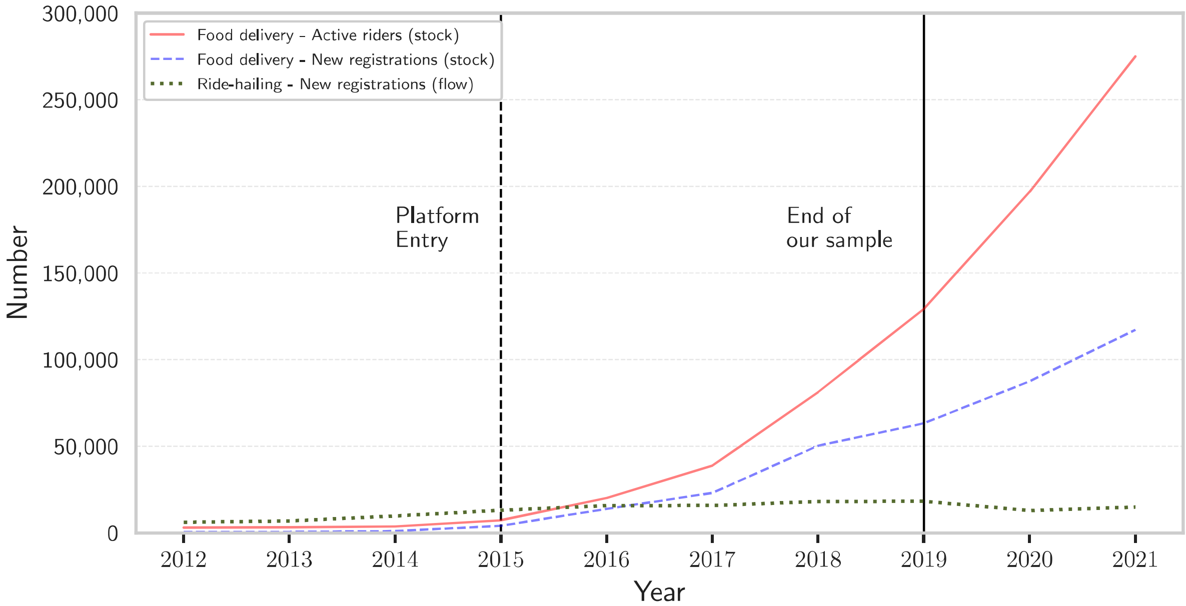
[36] Until 2018, a full year without any declaration led to automatic inactivity. Since then, the threshold is 24 consecutive months of non-declaration.

[37] Regime updated in January 2020; see https://www.economie.gouv.fr/entreprises/securite-sociale-independants, last accessed October 2025.

Throughout our study period (2012–2019), turnover reporting was self-declared and platforms did not transmit earnings to URSSAF.[38] These features help explain why revenue figures for riders in INSEE's *Base non-salariés* are incomplete or under-estimated. A government report from the Observatory on Undeclared Work (*Observatoire du travail dissimulé*) finds in 2019 that 38.4% of riders reported no turnover to URSSAF despite having platform transactions, and 47.4% reported positive turnover, but less than 95% of the amount generated on the platform (under-reporting). For these 85.8% of riders, the gap between the revenue generated on the platforms and that declared to URSSAF represents €189.7 million, corresponding to €24.3 million in contributions (applying the average contribution rates apparent in this sector).[39]

G Food-Delivery and Ride-Hailing in France

Figure A3: Food-Delivery and Ride-Hailing Registrations in France, 2012–2021



New (flow) and Registered (stock) Food-Delivery Workers and Ride-Hail Drivers

Notes: This figure extends Panel B of Figure 1 by adding ride-hailing registrations and by continuing the series beyond 2019. It reports annual new registrations and the stock of registered active food-delivery workers, together with new ride-hailing registrations. The solid vertical line at 2019 marks the end of the estimation sample and the onset of the COVID-related expansion. Ride-hailing registrations grow very little prior to 2019, whereas food-delivery registrations increase sharply following platform entry, indicating that delivery—not ride-hailing—drives the expansion of gig work during our sample period.

H Food-Delivery Platform Rollout in France

Food-delivery platforms entered the French market in 2015 and then expanded rapidly. Coverage increased from 11 cities in 2015 to roughly 400 by 2019. Table A4 lists the 15 most populous cities and the year of platform entry.

[38] More recently, legal changes have introduced platform reporting of users' earnings.

[39] Source: https://www.strategie-plan.gouv.fr/publications/observatoire-travail-dissimule.

Table A4: The 15 Most Populous Cities in France and the Date of Platform Entry

Commune	Department	Population 2015	Population 2019	Rank 2019	Entry Year
Paris	Paris	2,206,488	2,165,423	1	2015
Marseille	Bouches-du-Rhône	861,635	870,731	2	2016
Lyon	Lyon Metropolis	513,275	522,969	3	2015
Toulouse	Haute-Garonne	471,941	493,465	4	2016
Nice	Alpes-Maritimes	342,522	342,669	5	2016
Nantes	Loire-Atlantique	303,382	318,808	6	2015
Montpellier	Hérault	277,639	295,542	7	2016
Strasbourg	Bas-Rhin	277,270	287,228	8	2016
Bordeaux	Gironde	249,712	260,958	9	2015
Lille	Nord	226,014	232,741	10	2015
Rennes	Ille-et-Vilaine	215,366	220,488	11	2016
Reims	Marne	184,076	181,194	12	2017
Toulon	Var	167,479	178,745	13	2017
Saint-Étienne	Loire	171,057	173,821	14	2018
Le Havre	Seine-Maritime	172,366	168,290	15	2018

Source: French census (INSEE) for 2015 and 2019. Platform entry years by city are from the authors' compilation.

I Data: Definitions and Sources

I.1 Delivery Riders

To identify delivery riders and obtain their demographic characteristics, we combine information from three complementary French administrative databases: the Sirene business registry, the Self-employed Database (*Bases Non-Salariés*), and the All Active Workers Panel (*Panel Tout Actif*). These datasets provide different but overlapping perspectives on the population of micro-entrepreneurs operating in the delivery sector, allowing us to construct a comprehensive picture of rider demographics and employment.

I.1.1 Sirene

The Sirene database, which is France's business registry, is openly accessible online. It is organized at the legal unit level, encompassing both legal persons (distinct from their owners) and natural persons conducting economic activity. We identify delivery riders as establishments classified under NACE code 53.20Z ("Other postal and courier activities") with no employees (self-employed). The database provides (i) establishment-level information, including registration year, legal status, activity codes, and geographic location (city), as well as (ii) information about natural persons, such as first names and registered address. However, names and precise geolocation (finer than the city level) of a small number of riders are not released (see the main text for precise numbers).

I.1.2 Self-employed Database (SED)

The Self-employed Database (SED) complements Sirene by providing annual demographics and employment information for self-employed workers. It compiles data from social-security declarations. While Sirene is openly accessible, SED requires authorization and must be accessed within the CASD (*Centre d'accès sécurisé aux données*) secure environment.

SED uses the same firm identifier as Sirene, enabling us to match the two datasets. Between 2012 and 2019, we identify 147,923 unique riders aged 16-54, 97% of whom are also listed in Sirene. SED adds information on riders' turnover and demographics (French-born, foreign-born, age). However, as noted in Section F, turnover figures are severely misreported during our study period.

I.1.3 All Active Workers Panel (AAWP)

The All Active Workers Panel (AAWP) allows us to document riders' job trajectories prior to delivery work. This longitudinal dataset follows one-eighth of the active population (employees and self-employed) through spells of employment and self-employment.[40] Like the Self-employed Database, AAWP requires authorization and must be accessed within the CASD.

We identify individuals who created a micro-enterprise under activity code 53.20Z with no employees after 2015. Using their unique identifiers, we reconstruct their complete employment history before and after their delivery work. Because the AAWP covers only a one-eighth sample of active workers, it captures a representative subset, but not the entirety, of riders. These trajectories enable us to analyze patterns of entry into delivery work and the professional backgrounds of platform workers.

I.2 Police and Court Data

We use two complementary administrative sources of crime data. First, *police* records provide annual counts of criminal incidents brought to police attention. These data are aggregated at law enforcement jurisdictions since 2012 and offer a geographic coverage of crime at the initial contact point with the criminal justice system.[41] Police data, however, contain no individual-level information about offenders.

Second, we use *court* records to address this limitation. The judicial dataset *Cassiopée* provides detailed individual-level information on persons prosecuted in criminal cases, including offense type, offender characteristics, and case outcomes. However, *Cassiopée* has scope limits. It excludes cases dismissed by prosecutors and does not cover the most serious cases handled by higher criminal courts (assize courts, criminal courts, and courts of appeal).

Given these complementary strengths and limits, we rely primarily on police data for overall crime estimations and use judicial data to analyze heterogeneity across specific population groups.

I.2.1 Police Data

We rely on annual police-recorded data to construct local crime rates per 10,000 population.[42] These records cover incidents independent of subsequent judicial proceedings. Incidents are collected by police authorities.[43] Incidents enter the system through two

[40]The panel includes individuals born in selected reference months, representing roughly one-eighth of the French working population.

[41]By "initial contact point," we mean incidents recorded by police at first reporting or detection (e.g., victim reports, police stops, arrests) before prosecutorial screening or any judicial proceedings.

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

[43]For simplicity, we use "police" to denote two different entities: police stations ("commissariats") and gendarmeries. They perform similar missions (law enforcement, public safety, and crime prevention), although they operate in distinct jurisdictions and fall under different ministries (the Ministry of the Interior of police stations, and the Ministry of Defense for gendarmeries operate.

channels: (i) reports by victims or third parties, and (ii) police-initiated discovery (e.g., patrols, stops, investigations).

Police data are recorded at the level of police jurisdiction, the most granular geographic unit available. Jurisdictions align with administrative boundaries and may cover parts of a municipality or groups of municipalities across metropolitan France. On average, one jurisdiction comprises about 50 municipalities and 93,844 inhabitants.[44]

We aggregate offenses by police jurisdiction into six categories: all crimes, violence against the person, destruction of property, low-skill theft, high-skill theft, and drug offenses. We distinguish low- from high-skill theft by required expertise: low-skill offenses are opportunistic and non-specialized (e.g., shoplifting, bicycle theft), whereas high-skill theft involves greater planning, coordination, or technical know-how (e.g., burglary). The aggregation is detailed in Table A5.

I.2.2 Court Data

The court data come from the judicial information system *Cassiopée*, which records decisions issued by magistrates in two courts of first instance: Juvenile Court and Criminal Court (see Figure A4).[45] The dataset provides detailed information on cases and offenders, including the offender's age at the time of the crime, nationality, and gender. Because of their sensitive nature, these data are accessible only within the CASD secure environment. The availability of offender characteristics allows us to analyze heterogeneity in criminal behavior across demographic and age groups.

However, the dataset has limitations related to data collection. First, *Cassiopée* does not cover the most serious criminal cases tried in the assize court (court of first instance), the court of appeals, or the supreme court (see Figure A4).

Second, it records only completed cases and omits dismissals (*non-lieu*). Because most offenses committed between 2012 and 2019 were likely resolved by 2022 (our last update), this should not bias our sample. Nevertheless, excluding dismissals creates a discrepancy with police data, which include all reported incidents regardless of prosecution status.

Third, *Cassiopée* classifies cases with NATAFF codes rather than the police État 4001. NATAFF codes are assigned at registration from the initial file and are not revised. They describe the *case* and not each offender. Despite this taxonomy difference, we map court records to the same six categories used for police data: all crimes, violence against the person, destruction of property, low-skill theft, high-skill theft, and drug offenses (see Table A6). Using this mapping, we aggregate case counts (originally dated and recorded at the municipality level) to the same spatial and temporal units as the police data to ensure comparability in estimation.

[44]Between 2012 and 2019, some jurisdictions were merged following municipal reforms and police reorganizations. To ensure consistency over time, we harmonize all units to the most aggregated boundaries observed during the period.

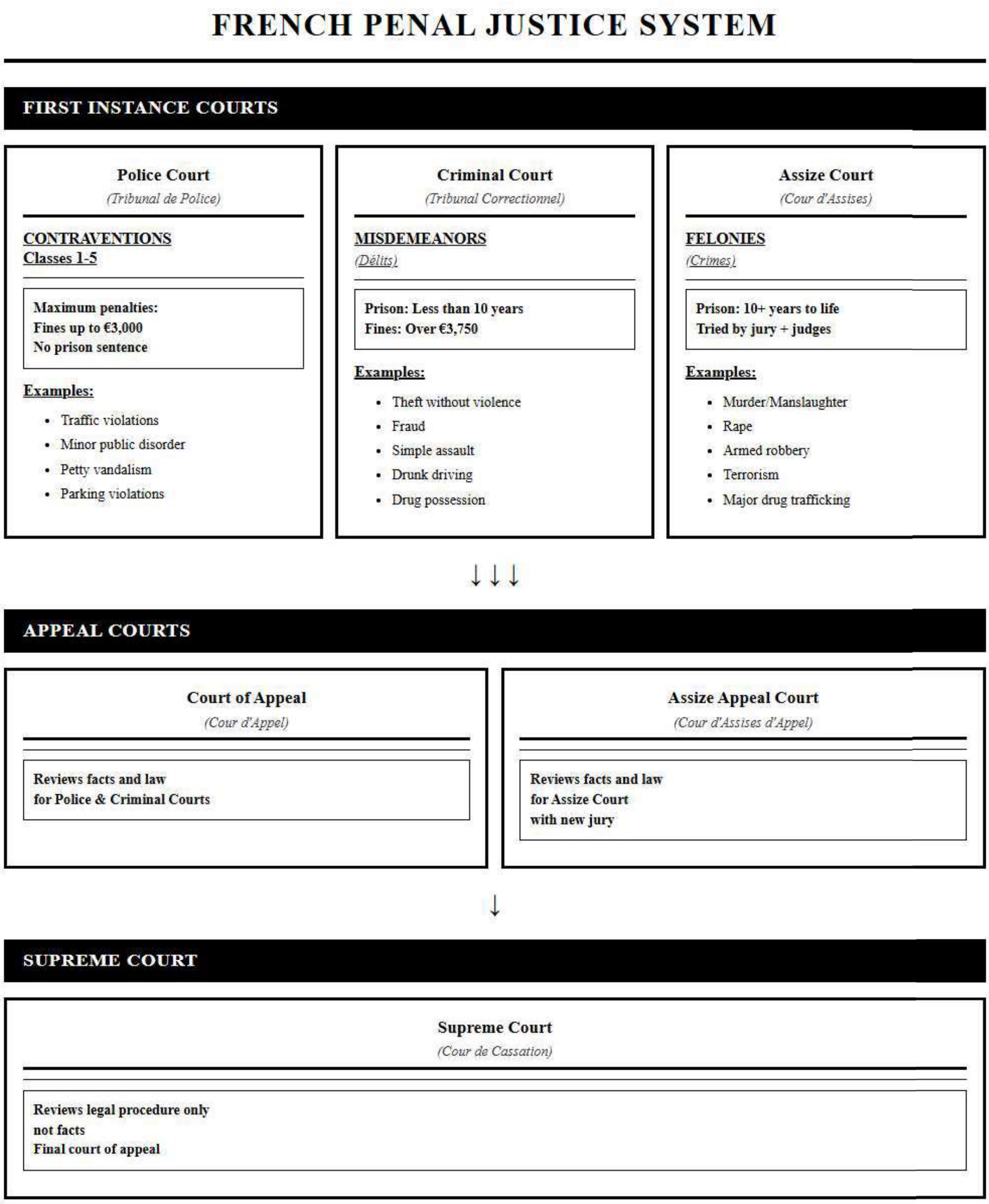
[45]Courts of first instance are the trial courts where cases are initially filed and adjudicated, before any appeal to higher courts (see Figure A4). Note that the Criminal Court is split between an adult division, trying adult defendants for misdemeanors, and a juvenile division, trying minors under specialized procedures and sanctions.

Table A5: Crime Categories in Police Recorded Data (État 4001 codes)

Crime Category	**Code**
All Crimes	
From "Settling of scores between criminals" to "Other offenses" (excluding codes 42-43)	1-107
Violence against the Person	
Settling of scores between criminals; Homicides and attempted homicides for thefts or other reasons; Voluntary assault and battery resulting in death; Other voluntary criminal or correctional assault and battery; Hostage-taking during thefts or for other purposes; Kidnappings; Threats or blackmail for extortion or other purposes; Armed robberies with firearms or bladed weapons against financial, industrial or commercial establishments, cash-in-transit companies, or individuals at home; Other armed robberies with firearms; Violent thefts without weapons on public roads or in other public places; Rapes or attempted rapes of adults or minors; Sexual harassment and other sexual assaults against adults or minors; Homicides of children under 15; Violence, abuse and abandonment of children; Violence against public officials	1-12, 15-26, 46-49, 51-52, 73
Destruction of Property	
Arson of public or private property; Other destruction and damage to public or private property; Destruction and damage to private vehicles	62, 63, 66-68
All Thefts	
Violent thefts without weapons on public roads or other public places; Burglaries of primary or secondary residences, industrial, commercial or financial premises, and other places; Thefts from vehicles; Shoplifting; Theft of cars or other vehicles; Armed robberies; Receiving stolen goods; Simple thefts against public or private establishments or individuals in public or private places.	25-41
Low-Skill Thefts	
Violent thefts without weapons on public roads or other public places	25, 26
Shoplifting	33
High-Skill Thefts	
Burglaries of primary or secondary residences; Burglaries of industrial, commercial or financial premises, or of other places	27, 28, 29, 30
Theft of cars or other vehicles	35-36
Drug Crimes	
Drug use and resale	56
Drug trafficking and resale without use; Drug use; Other drug law violations	55, 57, 58

Notes: État 4001 refers to the French national crime statistics classification system. Some crime codes may appear in multiple categories.

Figure A4: French Criminal Justice System



Notes: Schematic of the French criminal justice system. Our court data cover two of the first-instance criminal jurisdictions: the Police Court and the Criminal Court (adult and juvenile divisions).

Table A6: Crime Categories in Court Recorded Data (NATAFF codes)

Crime Category	**Code**
VIOLENCE AGAINST THE PERSON	
Rape and sexual assaults; assaults	A31-A32, A35-A39
DESTRUCTION OF PROPERTY	
Arson; Destruction of public and private property	B71-B73
LOW-SKILL THEFTS	
Purse-Snatching; Robbery; Shoplifting and pick-pocketing	B21-B22, B31

Notes: NATAFF refers to the French justice system nature of offense classification code.

J Average Statistics of Police Jurisdictions

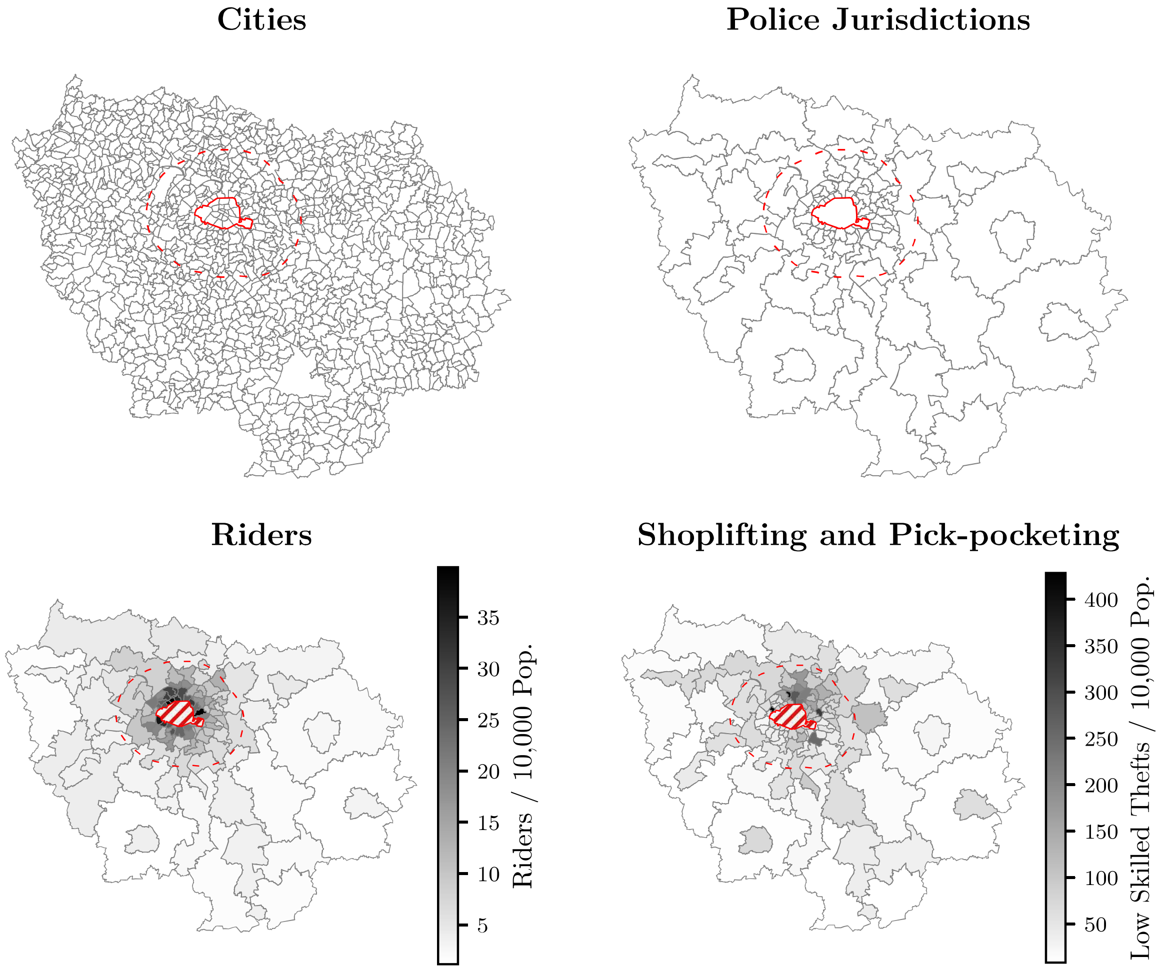
Table A7: Average Statistics of Police Jurisdictions by Treatment Status and Year

	Never Treated		Treated[a]	
	2014	2019	2014	2019
Population (aged 15-54)[b]	15,436	14,753	50,094	49,820
	Population Statistics (% population, 15-54)			
Men	50.37	50.52	49.87	49.90
Young (aged 15-24)	23.09	23.44	22.54	22.70
Migrants	8.61	9.68	9.94	10.76
Male migrants	4.23	4.84	4.79	5.22
	Labor-market Statistics (% population, 15-54)			
Delivery workers	0.01	0.03	0.01	0.17
Unemployment	12.51	11.89	11.39	10.87
Inactivity	5.76	6.49	4.68	5.20
Male unemployment	6.35	6.03	5.61	5.30
Male inactivity	3.04	3.51	2.40	2.72
Migrant unemployment	1.58	1.70	1.78	1.82
Migrant inactivity	0.72	0.99	0.77	0.92
Male migrant unemployment	0.76	0.80	0.81	0.80
Male migrant inactivity	0.36	0.55	0.39	0.48
	Crime Statistics (% population, 15-54)			
All crimes	10.48	11.89	9.96	10.63
Physical violence	1.48	2.26	1.44	1.88
Vandalism and destruction	1.17	1.17	0.89	0.84
Shoplifting and pick-pocketing	0.43	0.38	0.43	0.36
Burglary and vehicle theft	1.40	1.32	1.59	1.46
Drug use and resale	0.74	1.06	0.62	0.67

Notes: [a]Treated: A jurisdiction is treated between 2015 and 2019 if a food-delivery platform operates within the police jurisdiction, including a 15-km buffer around its boundary. [b]Population refers to the average number of residents aged 15-54. Other statistics are average rates per 100 inhabitants aged 15-54. See Section 5.3 and Appendix I for sources and definitions of population, labor-market and crime statistics.

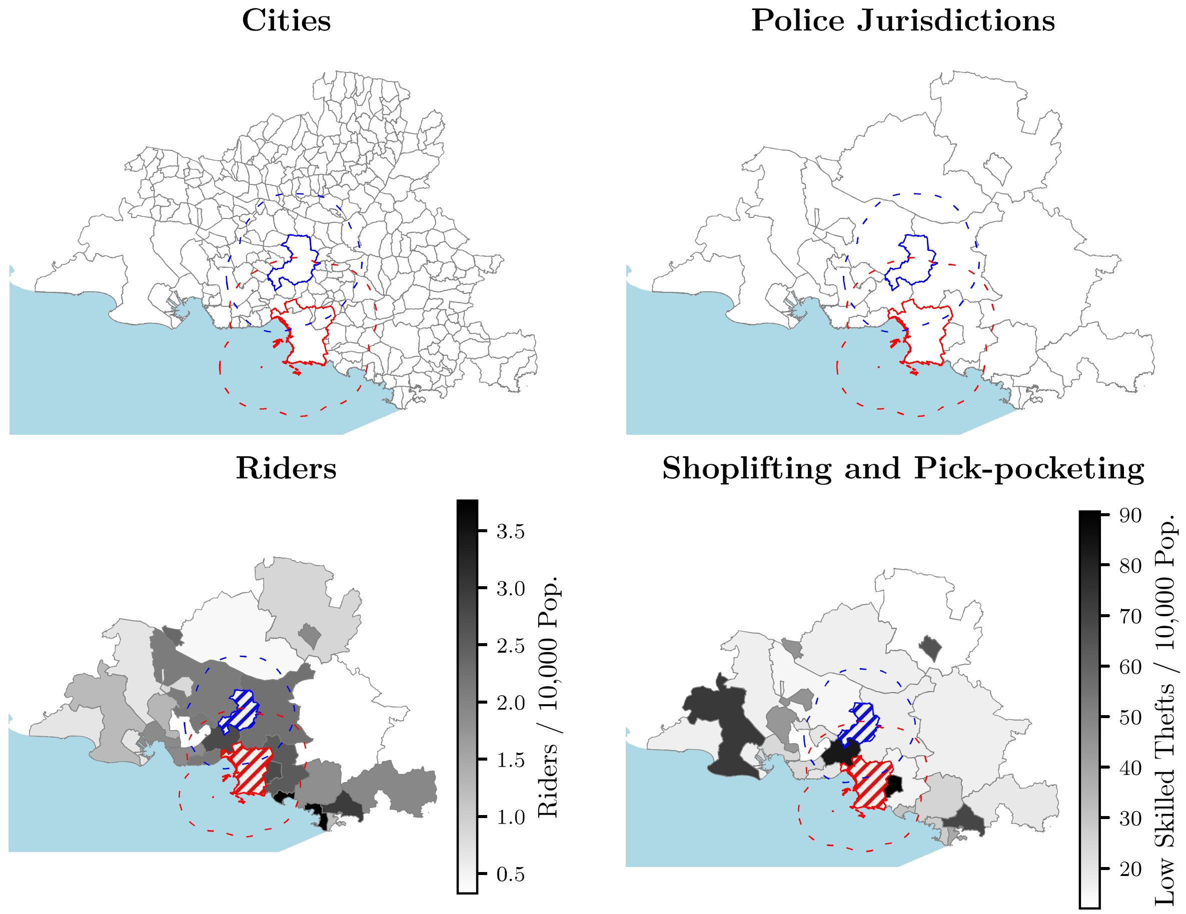
K Geographical Units and Outcomes

Figure A5: Paris and the Surrounding Area (2016)



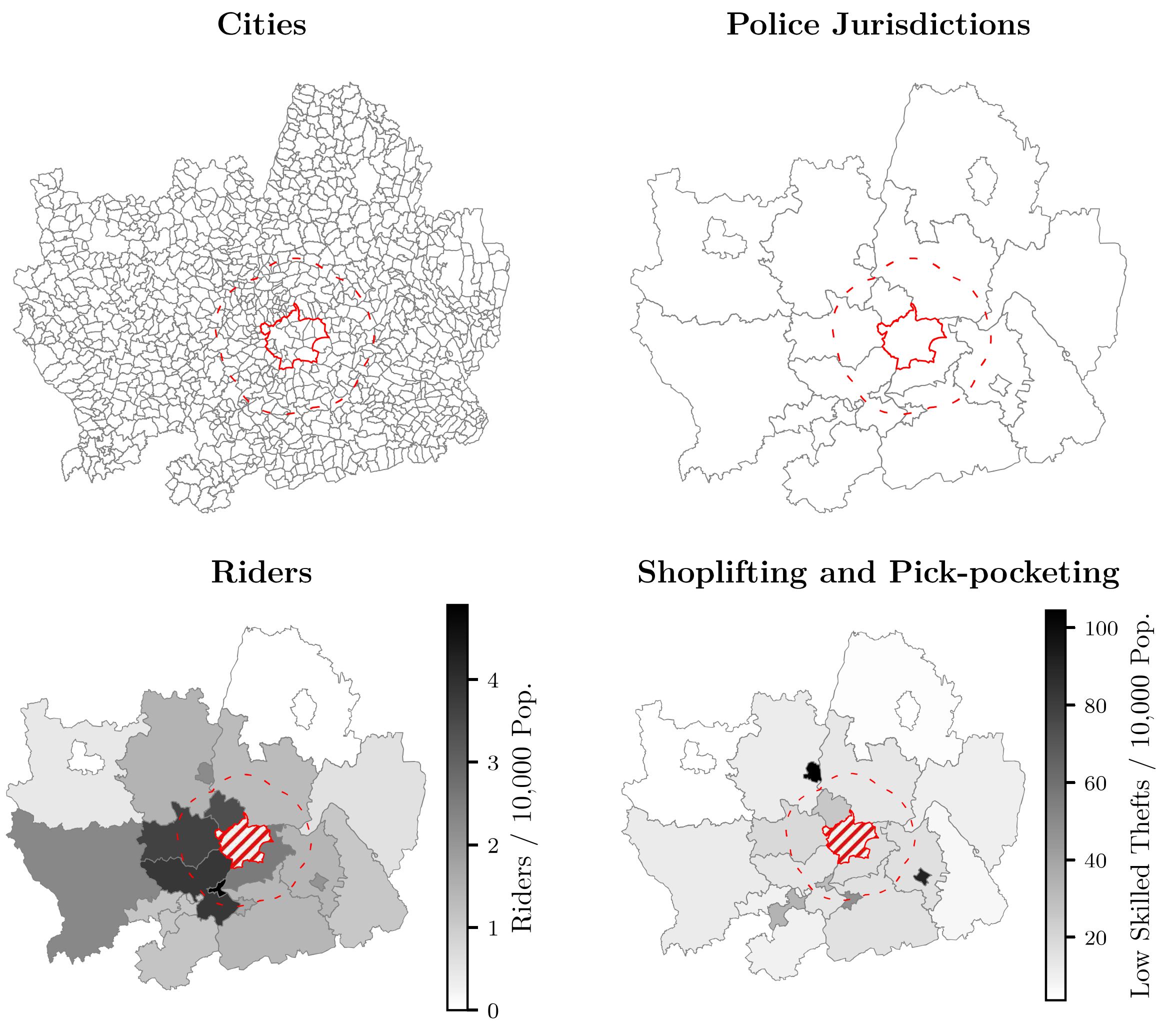
Notes: The red hatched area denotes the police jurisdiction of Paris, while the dashed red line represents a 15-kilometer buffer extending from that boundary. Grey lines denote city boundaries in the left graph of the first panel, while in the other maps they indicate police jurisdiction borders. The population aged 15–54 is used to compute the statistics presented in the second panel. Data on riders, shoplifting and pick-pocketing crimes, and population correspond to 2016, the year following the entry of delivery platforms into Paris. Statistics for Paris are excluded from the graphical representation to better highlight neighboring jurisdictions and potential spillover effects. Within the Paris police jurisdiction, there are approximately 50 riders and 122 shoplifting and pick-pocketing crimes per 10,000 inhabitants.

Figure A6: Marseille and the Surrounding Area (2017)



Notes: The red hatched area denotes the police jurisdiction of Marseille, while the dashed red line represents a 15-kilometer buffer extending from that boundary. Similarly, the solid blue line indicates the boundary of Aix-en-Provence, while the dashed blue line represents a 15-kilometer buffer extending from that boundary. Grey lines denote city boundaries in the left graph of the first panel, while in the other maps they indicate police jurisdiction borders. The population aged 15–54 is used to compute the statistics presented in the second panel. Data on riders, shoplifting and pick-pocketing crimes and population correspond to 2017, the year following the entry of delivery platforms into Marseille and Aix-en-Provence. Statistics for these cities are excluded from the graphical representation to better highlight neighboring jurisdictions and potential spillover effects. Within the Marseille police jurisdiction, there are approximately 11 riders and 81 shoplifting and pick-pocketing crimes per 10,000 inhabitants. Within the Aix-en-Provence police jurisdiction, there are approximately 15 riders and 56 shoplifting and pick-pocketing crimes per 10,000 inhabitants.

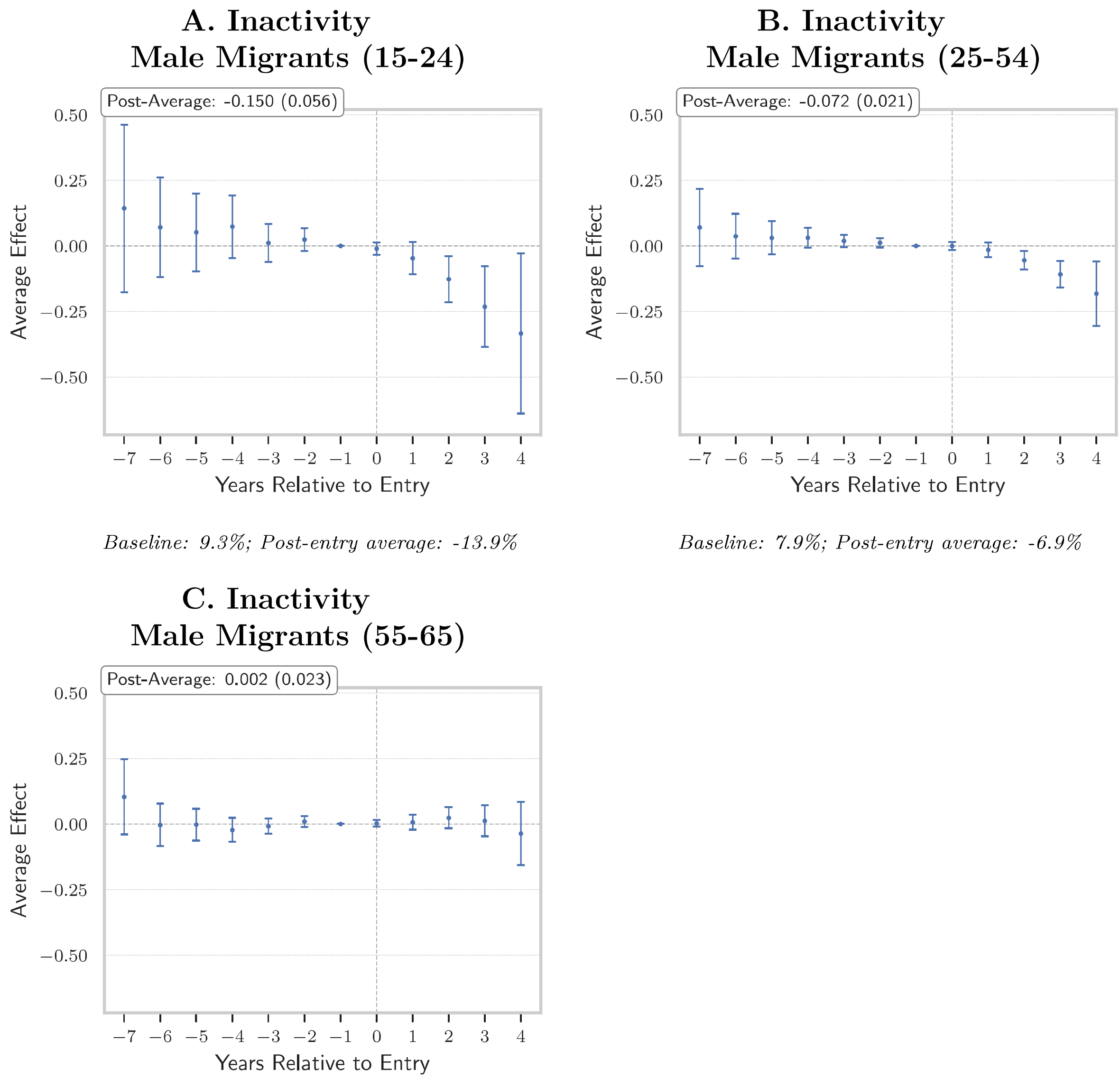
Figure A7: Lyon and the Surrounding Area (2016)



Notes: The red hatched area denotes the police jurisdiction of Lyon, while the dashed red line represents a 15-kilometer buffer extending from that boundary. Grey lines denote city boundaries in the left graph of the first panel, while in the other maps they indicate police jurisdiction borders. The population aged 15–54 is used to compute the statistics presented in the second panel. Data on riders, shoplifting and pick-pocketing crimes and population correspond to 2016, the year following the entry of delivery platforms into Lyon. Statistics for Lyon are excluded from the graphical representation to better highlight neighboring jurisdictions and potential spillover effects. Within the Lyon police jurisdiction, there are approximately 24 riders and 88 shoplifting and pick-pocketing crimes per 10,000 inhabitants.

L Male Inactivity by Age Category

Figure A8: Event Study - Inactivity of Male Migrants by Age Category

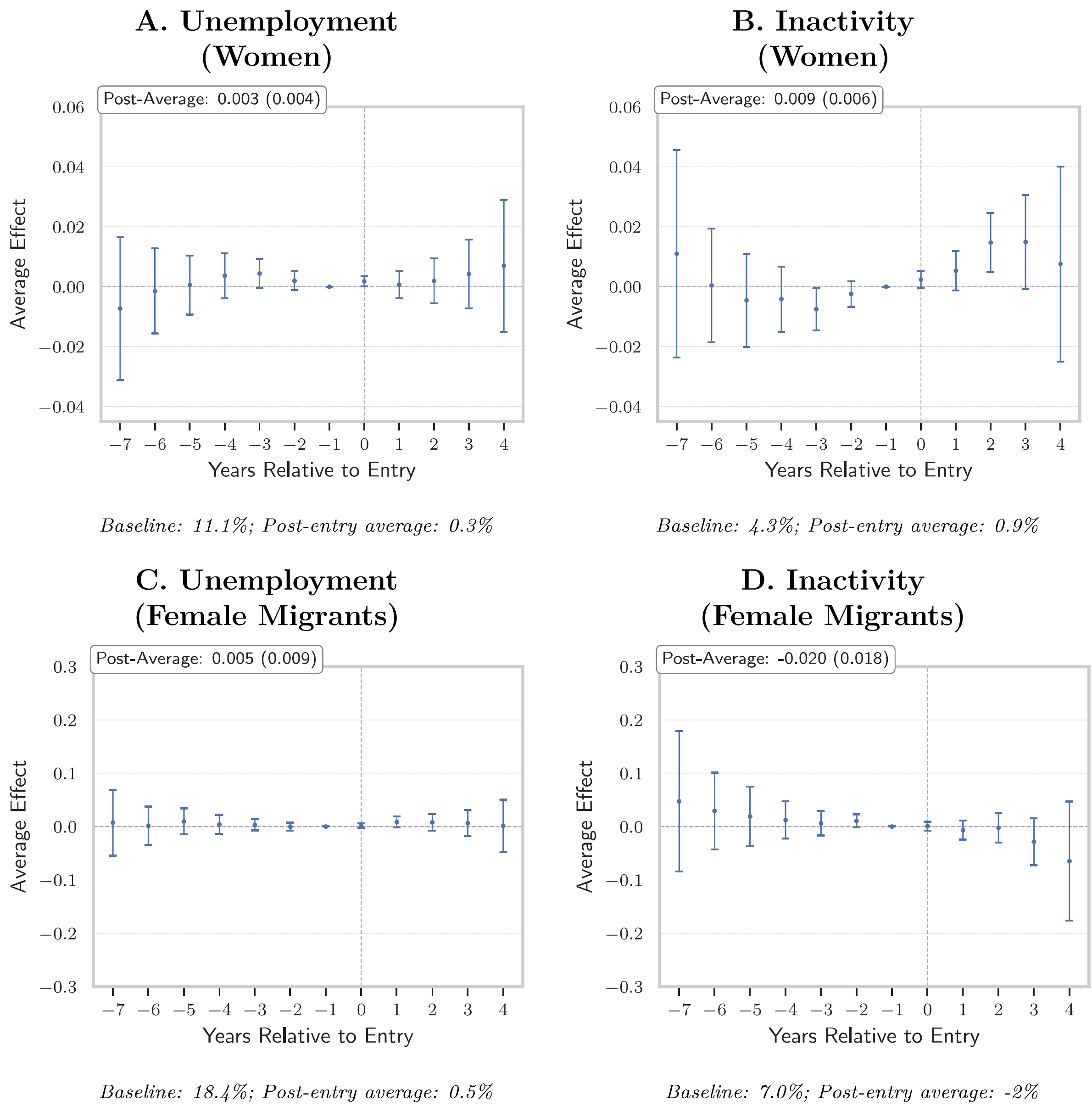


Baseline: 5.7%; Post-entry average: 0.0%

Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Baselines are from the 2014. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown. Jurisdictions excluded due to zero values in the outcome variable: 79 (Panel A), 4 (Panel B) and 8 (Panel C).

M Female Labor Market Outcomes

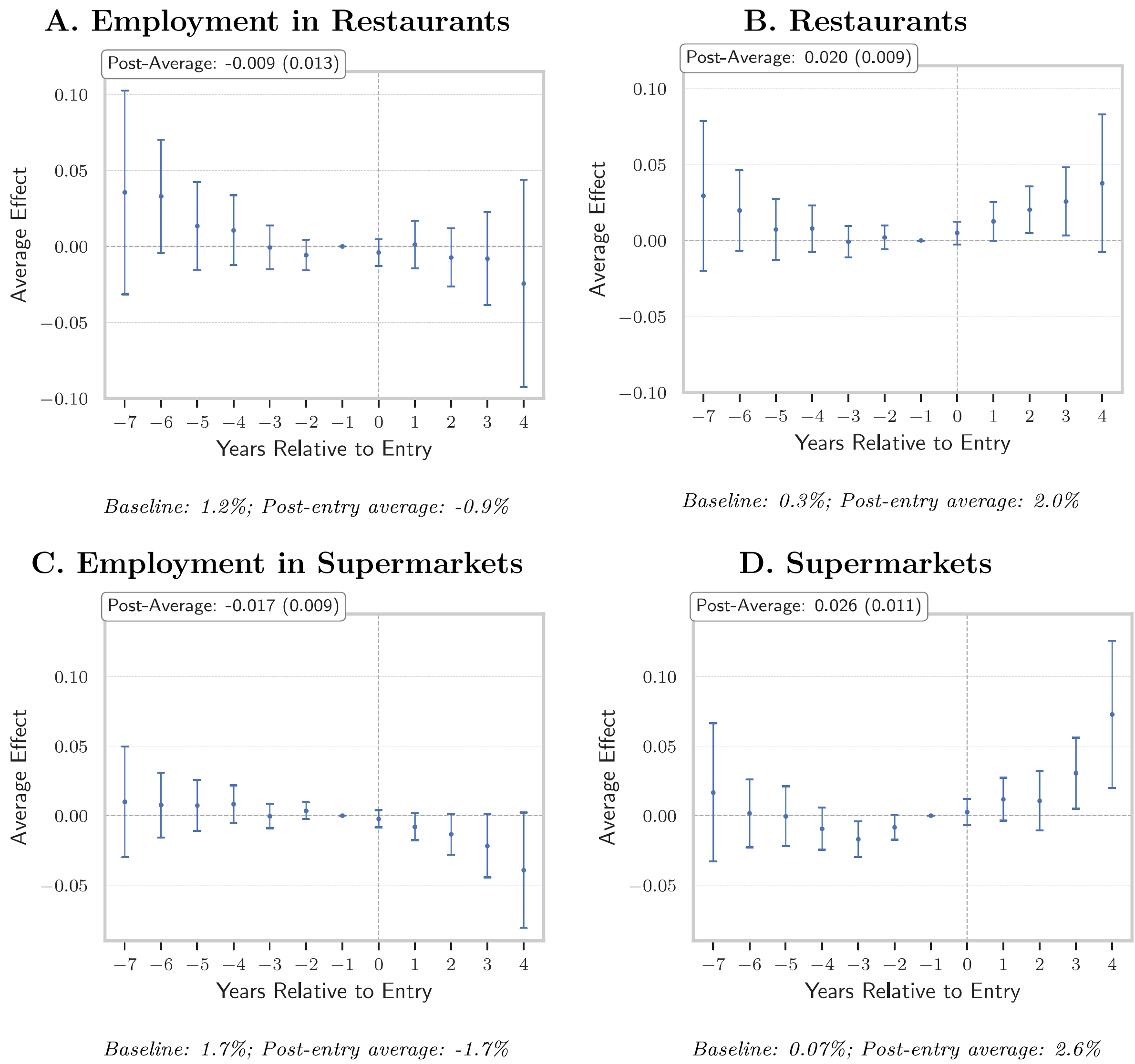
Figure A9: Event Study - Female Labor Market Outcomes



Notes: Event-study estimates from the Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry is defined as the first year in which a delivery platform operates within 15 km of the police jurisdiction boundary. The vertical dashed line marks the entry year (event time 0). Pre-entry coefficients (event times −7 to −1) assess parallel trends. Outcomes are in logs. Post-entry values show average treatment effects across post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown. Number of police jurisdictions excluded due to zero values in the outcome variable: 1 (Panel C) and 1 (Panel D).

N Local Shops

Figure A10: Event Study - Local Shops



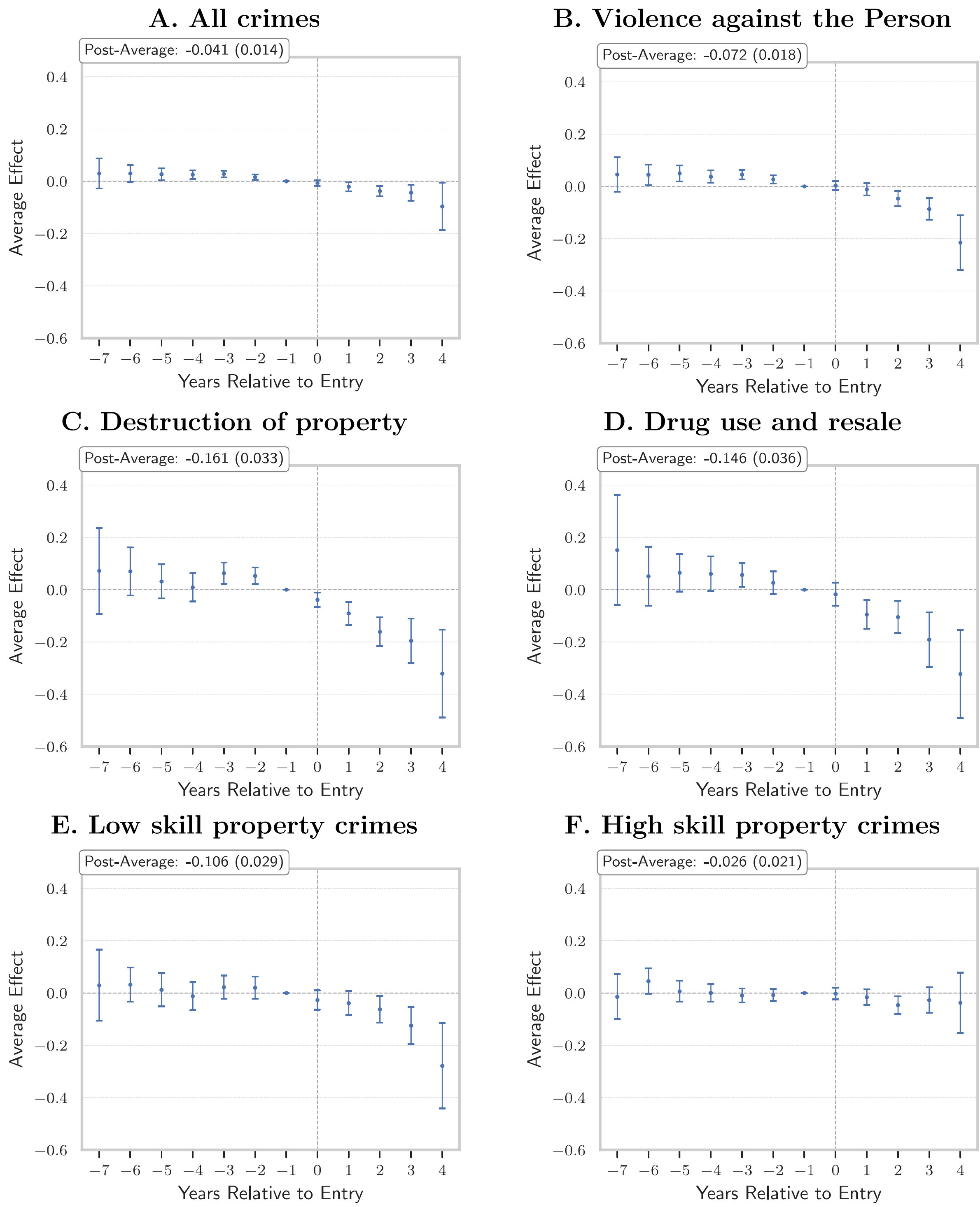
Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Baselines are from 2014. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown. Jurisdictions excluded due to zero values in the outcome variable: 3 (Panel C) and 3 (Panel D).

O Robustness: Drop Big Cities (Not Surrounding Areas)

Food-delivery platforms first enter larger markets, which indicate higher demand and a larger pool of potential workers. To account for this pattern, our staggered DiD analysis weights police jurisdictions by their 2012 population. However, this approach may introduce bias if our results are disproportionately influenced by a small number of highly populated jurisdictions. We therefore re-estimate our model excluding the most populous jurisdictions, specifically those covering Paris, Marseille, and Lyon, the three largest cities in France. These jurisdictions together represent 2.87 million working-age inhabitants out of 40.37 million across the 681 jurisdictions, with an average jurisdiction population of 59,293 working-age individuals in 2012.

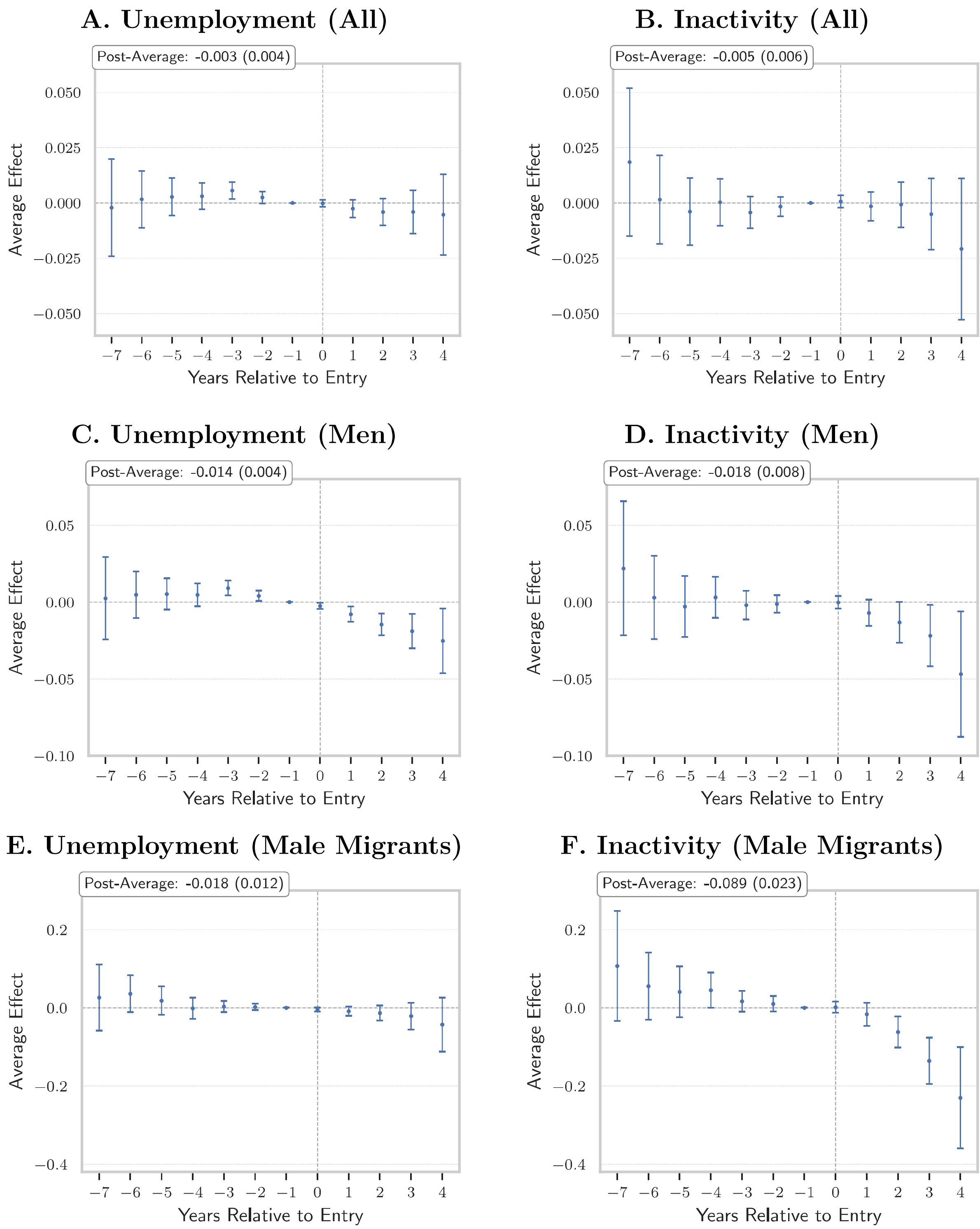
The figures below report the results after excluding these three major cities. The specification still retains treated jurisdictions within 15 km of these cities, as well as all other jurisdictions, consistent with the main estimation strategy. The estimates remain closely aligned with the baseline, confirming that large jurisdictions are not driving the main findings.

Figure A12: Event Study with Big Cities Excluded: **Crime Outcomes**



Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Police jurisdictions covering the three largest French cities (Paris, Marseille, and Lyon) are excluded. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown.

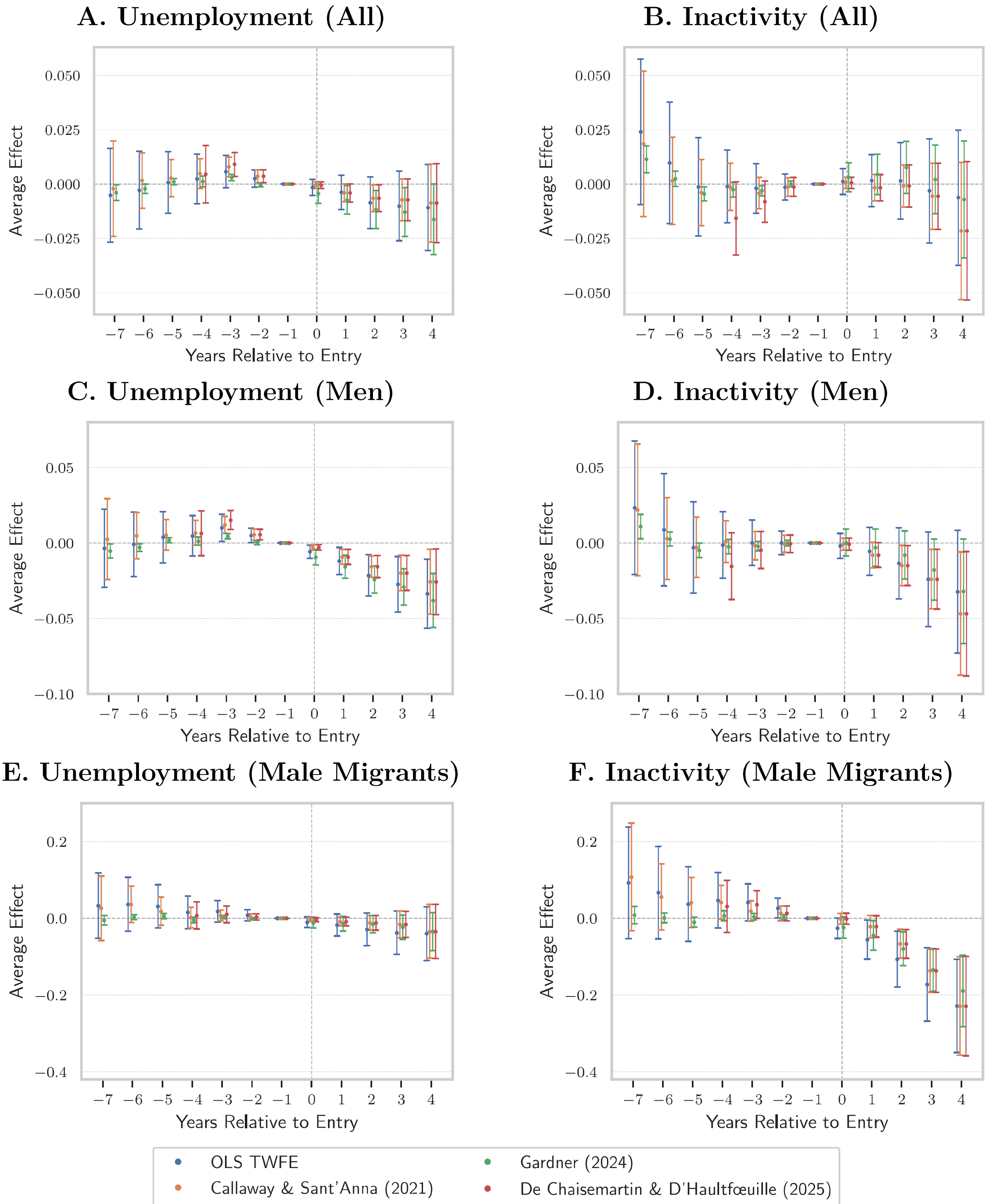
Figure A11: Event Study with Big Cities Excluded: **Labor Market Outcomes**



Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Police jurisdictions covering the three largest French cities (Paris, Marseille, and Lyon) are excluded. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown.

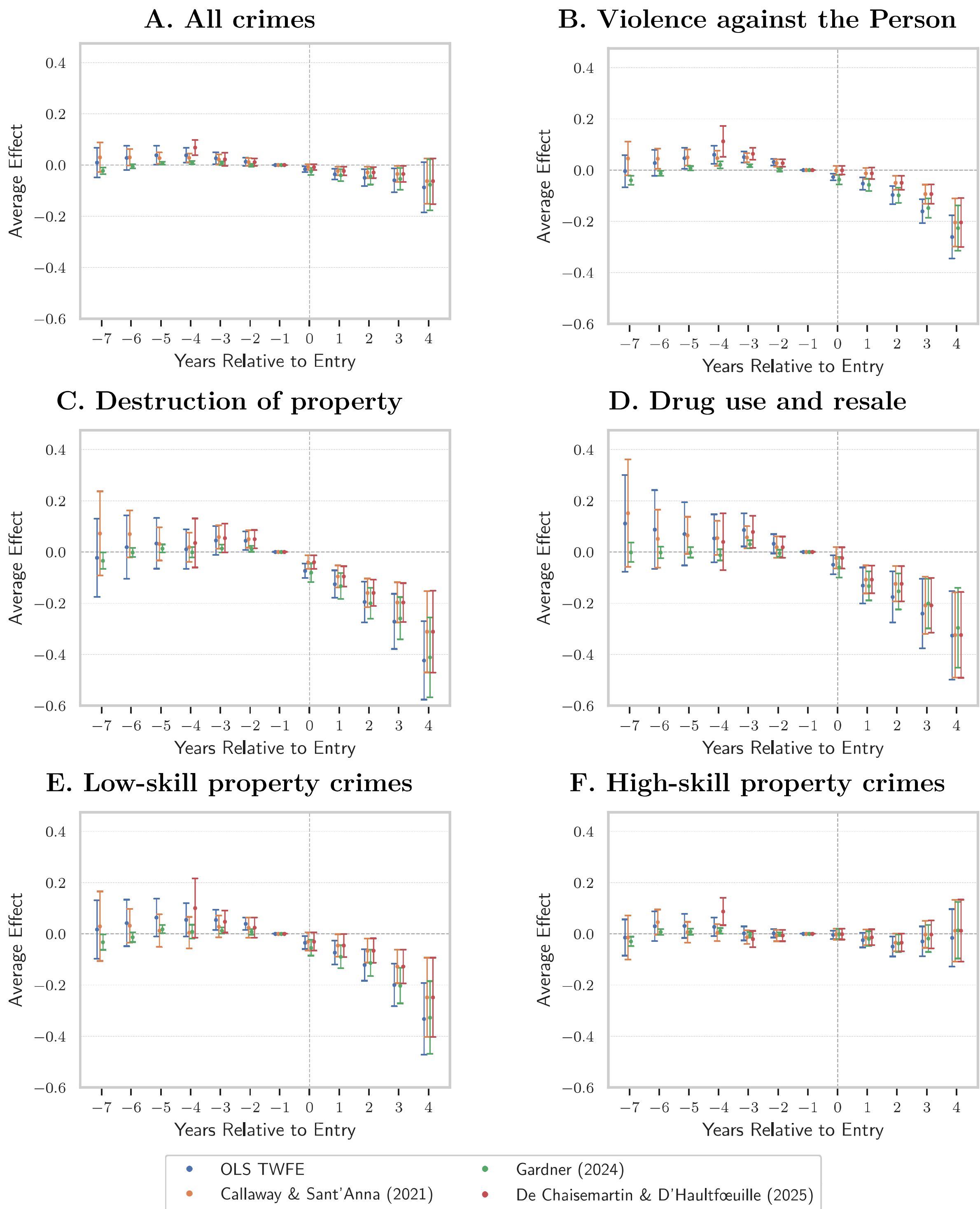
P Robustness – Alternative Estimators

Figure A14: Event Study with Alternative Estimators: **Labor Market Outcomes**



Notes: Event-study estimates from OLS two-way fixed effects (blue), Callaway and Sant'Anna 2021 (orange), Gardner 2024 (green), and de Chaisemartin and D'Haultfœuille 2025 (red) staggered DiD estimators. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Police jurisdictions covering the three largest French cities (Paris, Marseille, and Lyon) are excluded. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown.

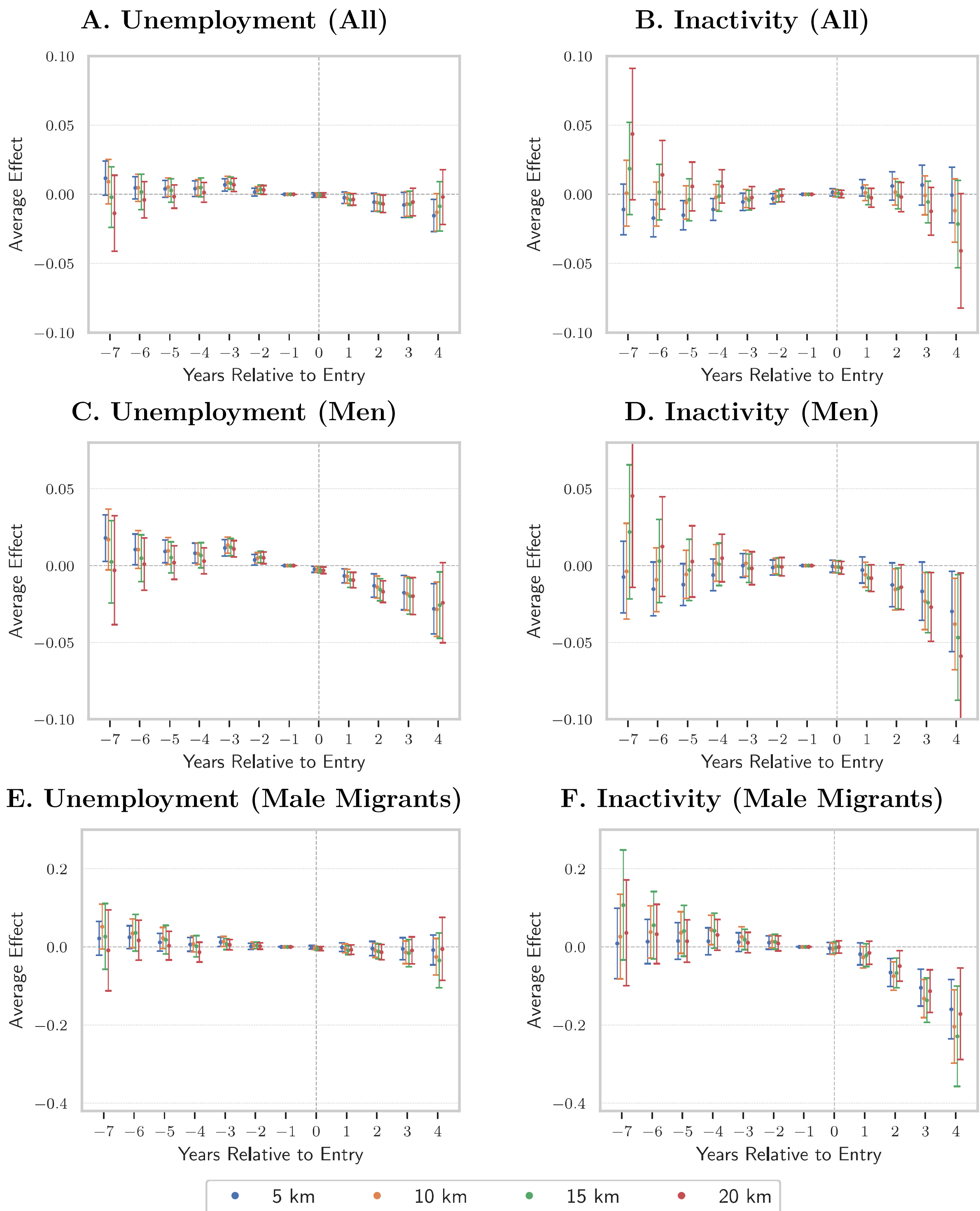
Figure A13: Event Study with Alternative Estimators: **Crime Outcomes**



Notes: Event-study estimates from OLS two-way fixed effects (blue), Callaway and Sant'Anna 2021 (orange), Gardner 2024 (green), and de Chaisemartin and D'Haultfœuille 2025 (red) staggered DiD estimators. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 15-km buffer around its boundary. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown.

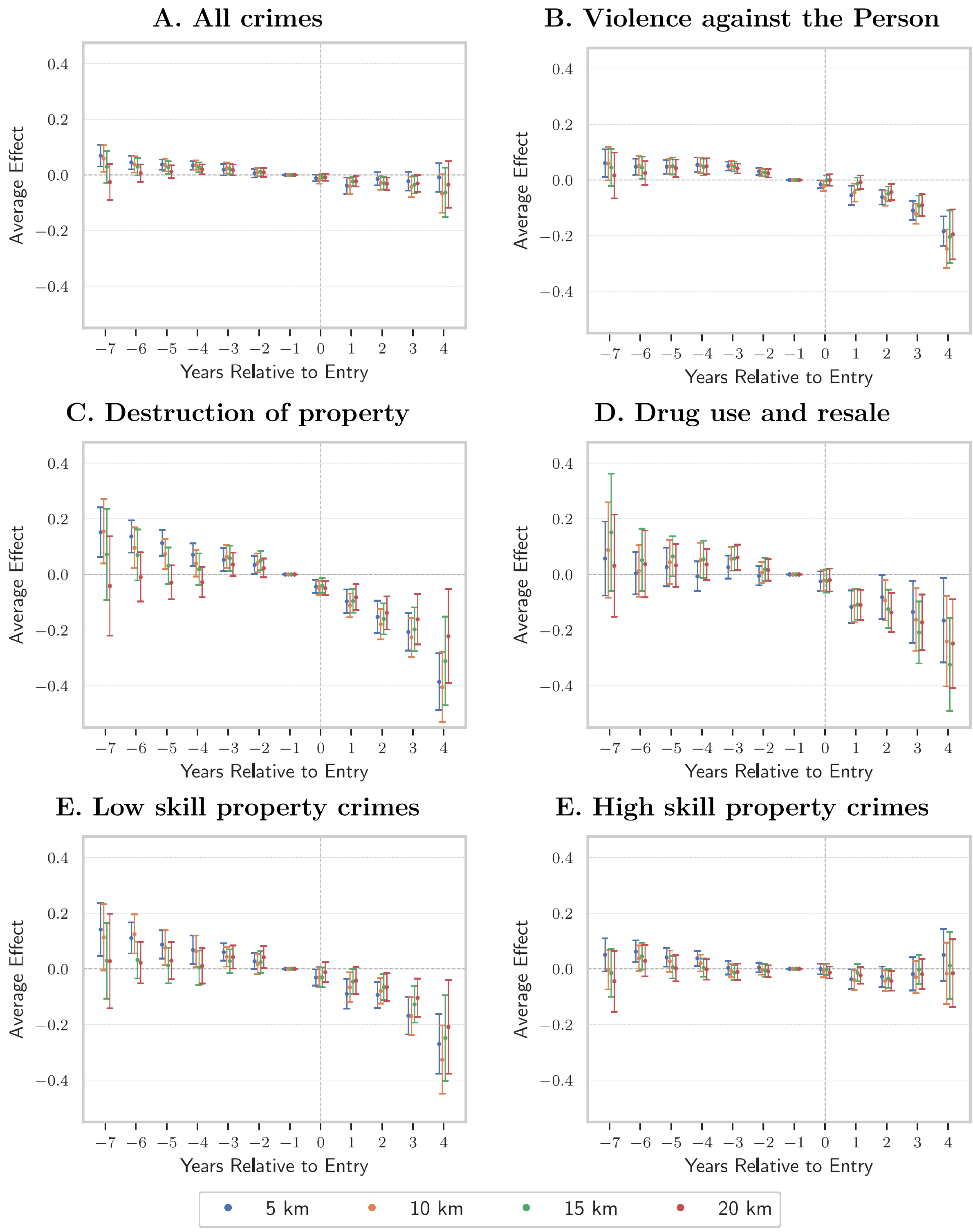
Q Robustness – Alternative Distances

Figure A15: Event Study with Alternative Distances: **Labor Market Outcomes**



Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 5, 10, 15, or 20-km buffer around its boundary. Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown.

Figure A16: Event Study with Alternative Distances: **Crime Outcomes**

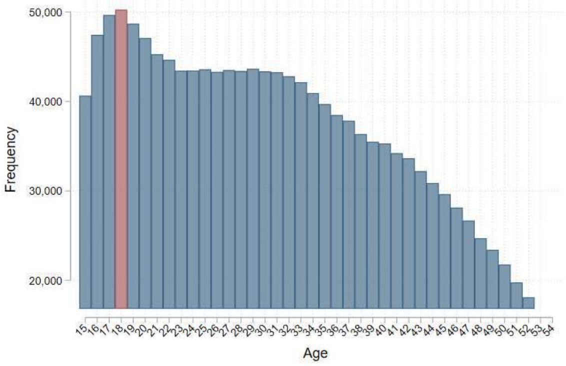


Notes: Event-study estimates from Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry: first year a food-delivery platform operates within a police jurisdiction, including a 5, 10, 15, or 20-km buffer around its boundary.Logged annual outcomes at the jurisdiction level for individuals aged 15-54. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$, across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown.

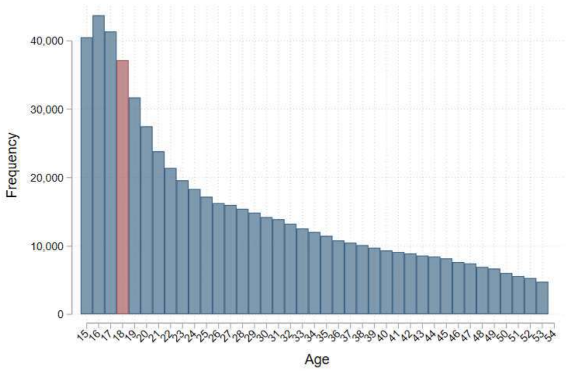
R Crime Age Distribution

Figure A17: Crime Age Distribution

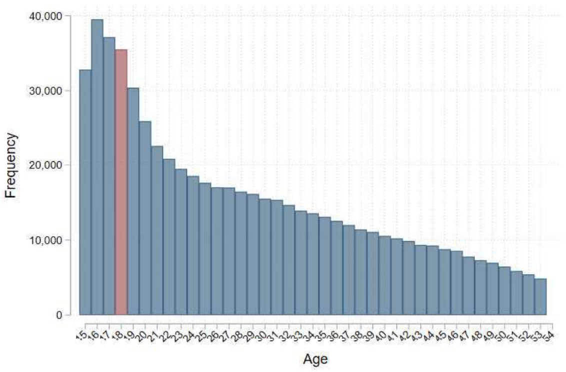
A. Violence Against the Person



B. Destruction and Damage of Property



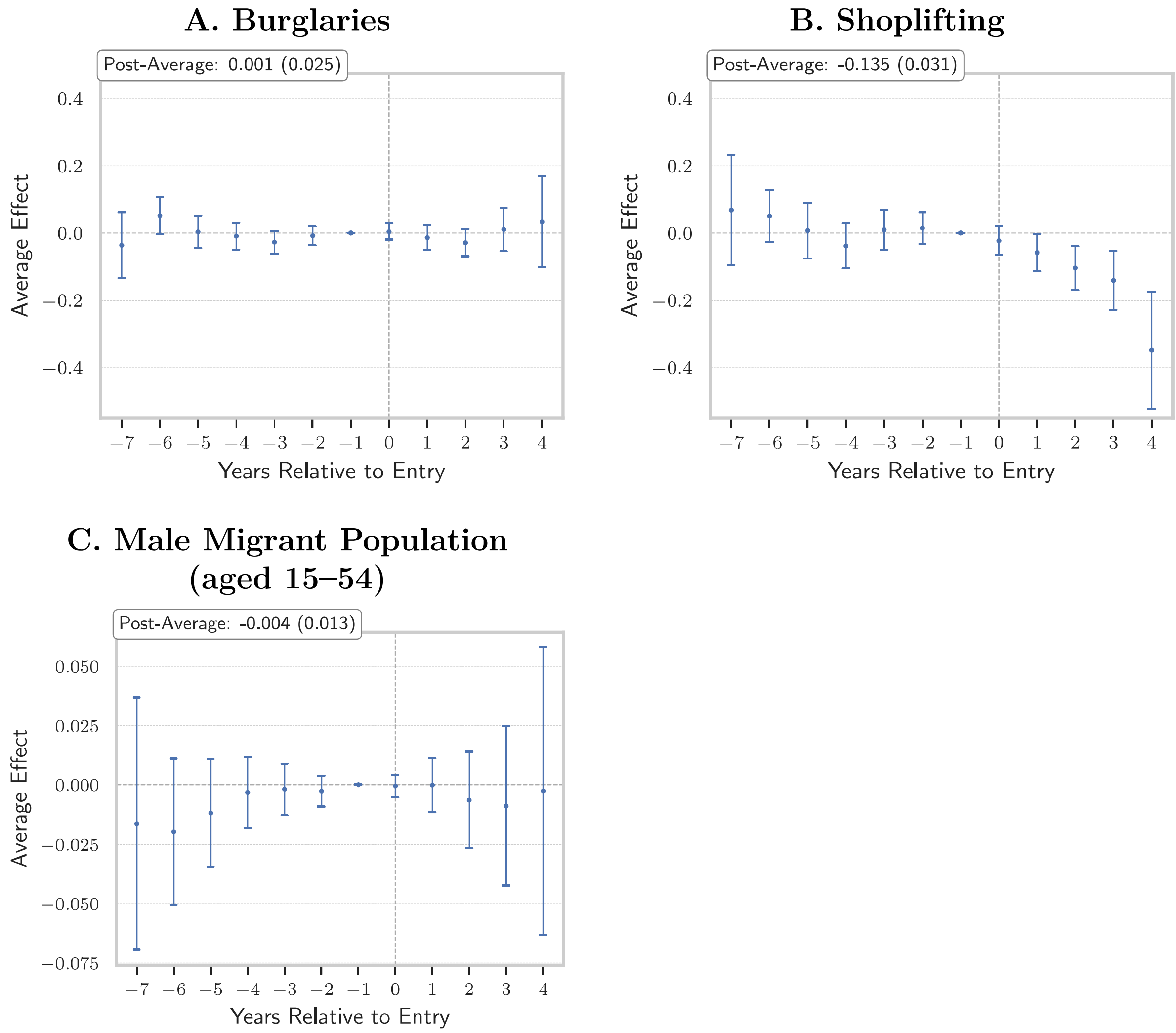
C. Low-Skill Theft



Notes: Age distribution of offenders across three crime categories: violence against the person (A), destruction and damage of property (B), low-skill theft (C). Data are based on court data from 2012-2019. The x-axis shows age in years, and the y-axis shows the frequency of offenses. The red vertical line marks age 18, representing the legal transition from minor to adult status in France.

S Movement as Confounder

Figure A18: Event-Study Evidence on Movement-Related Confounders



Notes: Event-study estimates from the Callaway and Sant'Anna (2021) staggered DiD estimator. Platform entry is defined as the first year a food-delivery platform operates within a police jurisdiction, allowing for a 15 km buffer around the boundary. Outcomes are logged annual jurisdiction-level measures for individuals aged 15–54. Panel C reports the log population of male migrants, testing for selective residential sorting following platform entry. The vertical dashed line marks event time 0. Post-entry averages are computed as $(\exp(\widehat{\text{Post-Average}}) - 1) \times 100$ across all post-entry years. Standard errors are clustered at the police jurisdiction level. 95% confidence intervals shown.