The Gig Economy and Crime*

Isadora Frankenthal

August 2025

Abstract

This study investigates how the expansion of gig work affects the level and geographic distribution of crime by leveraging the staggered rollout of the largest food delivery platform in Brazil (iFood), combined with the universe of geocoded property crime and robbery incident reports from São Paulo state. The rise in gig work reduced crime on average by 10.4%. The effect is larger in magnitude at times of day when the returns to delivery work are highest and in lower-income neighborhoods, where delivery workers disproportionately reside. There is no evidence that crime is displaced toward areas with high delivery demand.

*I am very thankful to Daron Acemoglu, Nikhil Agarwal, David Atkin, Abhijit Banerjee, Esther Duflo, Amy Finkelstein, Jon Gruber, Nathan Hendren, Simon Jäger, Horacio Larreguy, Joana Monteiro, Jacob Moscona, Ben Olken, Vítor Possebom, Vincent Rollet, Pedro Sant'Anna, Frank Schilbach, Vanessa Sticher, Joule Voelz, and participants at the MIT Development Workshop, the MIT Trade Workshop, and the RIDGE Forum on the Economics of Crime for their feedback. I also thank the George & Obie Shultz fund for providing resources to purchase the e-receipt data, and João Branco, Debora Gershon, and Marina Merlo for their help with the iFood data.

1 Introduction

The digital revolution of the twenty-first century has led to new, nontraditional work arrangements, commonly referred to as "gig" work. These jobs are mediated by digital platforms and allow workers to flexibly choose when and how much to work. The increase in gig work, and in particular jobs provided by transportation and delivery platforms, has quickly transformed labor markets for low-skilled workers. In Brazil, the setting of this study, transportation and delivery apps employed approximately 1.5 million drivers in 2022—a figure that grew by 984% over the previous five years (IPEA, 2022). This represents 31% of the population employed in the transportation sector, roughly 1% of the total workforce, and a much larger share of low-skilled employment.

This study investigates the impact of this rapid rise of flexible employment on crime. *Ex ante*, this relationship is unclear. On the one hand, economic models of crime assume the choice between crime and employment is mutually exclusive and predict that positive labor market shocks reduce crime because they increase the opportunity cost of criminal activity (Becker, 1968). The growth of delivery jobs, the focus of this study, was a positive labor market shock to young and unskilled men, the population most likely to commit "blue-collar" crime. From this perspective, the rise of gig work may have precipitated a large reduction in crime. On the other hand, flexibility may increase free time and make employment easier to combine with criminal activity, potentially raising crime (Jacob and Lefgren, 2003; Dahl and DellaVigna, 2009). Moreover, flexible employment may shift not only the *level* of crime but also its distribution across space: delivery work shifts the location of employment, as low-skilled workers who would otherwise likely work in lower-income neighborhoods are hired to deliver goods all over the city. This could relocate crime by expanding opportunities to engage in criminal activity, especially in geographically segregated cities where mobility is otherwise limited. It is therefore necessary to turn to data in order to understand how the introduction of flexible and mobile delivery work affects crime.

I exploit the staggered expansion of Brazil's largest food delivery platform, iFood, across municipalities in São Paulo—the country's most populous state—to examine how the growth of platform work affects both the level and spatial distribution of crime. São Paulo provides an ideal setting: it contains numerous large cities with high crime rates and strong demand for delivery services, while also offering unusually rich crime data that include all instances of larceny/theft, burglary, and robbery, and are geocoded, time-stamped, and reliable. These features allow me to study not only the overall impact of gig work on crime, but also the channels through which this effect operates.

Combining ten years of data on incident reports with the staggered timing of the introduction of iFood across municipalities in a difference-in-differences framework, I find that the introduction of the delivery platform reduces municipality-level criminal offenses by 10.4%, with no spatial spillovers to neighboring municipalities. This is equivalent to 529 fewer offenses per municipality-year on average. This negative effect extends to violent property crime, when there is use of force or a weapon. The effect increases over time, consistent with the ramp-up in demand following iFood's initial entry.

The reduction in crime I find is noteworthy, as public policies that effectively improve public safety are rare, especially in Latin America and other developing regions where crime levels are persistently high (IADB, 2015; IPA, 2021).

Having documented that the effect of the expansion in delivery work on crime is negative, I turn to the mechanisms behind the effect. Economic models of crime contend that positive labor market shocks reduce crime by increasing its opportunity cost (Becker, 1968; Ehrlich, 1996). However, isolating this channel is typically challenging because such shocks often also affect other determinants of crime, such as leisure time, mental well-being, and income (Rose, 2018). Two unique features of food delivery work make it possible for me to look for evidence of the opportunity cost channel. First, delivery drivers are completely free to choose when to work during the day, and second, iFood deliveries are concentrated around mealtimes, meaning that the returns to work (and therefore the opportunity cost of crime) vary *predictably* across the day. I test for this channel by using information on the exact time when each offense was committed to disaggregate the main effect by time of day. If the increase in the opportunity cost of crime is driving the results, effects would be stronger at times when returns to delivery work are higher. Although effects are present when delivery demand is low—consistent with an effect of total income on criminal participation—effects are significantly stronger when delivery demand is highest, particularly for violent crime. This suggests that potential offenders factor in hour-by-hour opportunity costs, and that policies offering alternative financial opportunities could be most effective if timed to coincide with peak-crime periods.

I then use the geocoded incident report locations to examine the spatial incidence of the effect of delivery job expansion on crime within municipalities. The average municipality-level effect could mask large differences across neighborhoods for two reasons. First, separate work in criminology has documented that offenders rarely travel long distances to commit crime, suggesting the effect could be stronger in lower-income neighborhoods where delivery drivers disproportionately live and work (e.g. Rengert, 2012). Using gridded data on income per capita, I find that the effect is indeed strongest in the lowest-income neighborhoods. The poorest quartile of neighborhoods register 50% more crime per capita than the richest quartile at baseline, which means that the shock is dampening the inequality in safety across neighborhoods. Second, delivery work is concentrated in areas with high demand for services, which could raise crime in those locations—particularly in spatially segregated cities where mobility is more limited. I re-estimate the effect using only the 1 km^2 grid cells that received deliveries during the study period and find the effect is virtually identical to the main result, including in municipalities with above-median income inequality where segregation is most pronounced. In other words, I find no evidence of relocation toward high-delivery neighborhoods, inconsistent with anecdotal accounts from the Brazilian media (see Figure A1).

Related Literature This project contributes to past work examining the economic impacts of gig work (e.g. Chen et al., 2019; Angrist et al., 2021; Cook et al., 2021; Scarelli, 2024; Papp, 2024;

Plotkin, 2024).[1] To my knowledge, this is the first paper to investigate the effect of gig work on crime, which is important given the rapid and widespread rise of flexible jobs and potential competing effects of the availability and flexibility of work on criminal activity.

The results also add to the existing evidence on the relationship between labor market conditions and crime. Financially-motivated crime has been shown to increase following mass layoff events (Khanna et al., 2021; Britto et al., 2022) and episodes of trade liberalization (Dix-Carneiro et al., 2018; Dell et al., 2019) in different Latin American countries.[2] This paper extends this evidence by examining the market-level effect of a large shock to flexible jobs, which have become increasingly common in the last decade and could be very different from the effect of shocks to traditional, full-time employment. A small related literature investigates the determinants of the spatial distribution of crime inside cities, such as density and transportation (Glaeser et al., 1996; Khanna et al., 2022; Lafrogne-Joussier and Rollet, 2023). This study also documents how shifts in the location of low-skilled work affects the geographic distribution of crime.

Finally, this paper relates to existing work on the causes of Latin America's persistently high crime rates and the effects of public policies aimed at reducing them (e.g., Mejia and Restrepo, 2013; Monteiro et al., 2020; Blattman et al., 2021, 2022; Egger, 2022; Sviatschi, 2022; Pezzuchi et al., 2024; Guerra et al., 2025; Mancha et al., 2025). Most policies that successfully reduce crime rely on increasing police presence or pacifying gang-controlled territories, but these strategies are costly and can often either displace crime to other areas or backfire (see Bellégo and Drouard, 2024). The finding that the expansion of gig jobs significantly reduces crime suggests an alternative way to improve public safety by guaranteeing an easily accessible source of income to low-skilled individuals.

The paper is organized as follows. Section 2 describes the introduction of the delivery platform and the data. Section 3 introduces the empirical strategy and reports the main results. Section 4 investigates mechanisms, and the last section concludes.

2 Background and Data

2.1 The Delivery Platform as a Labor Market Shock

iFood introduced its delivery platform in 2012, the first of its kind in Brazil, and has grown rapidly since. It currently has about 63 million users and 87% of the food-delivery market.[3] In 2020, iFood employed 537,964 delivery drivers (roughly 0.5% of the Brazilian workforce) (Haddad et al., 2023). Registration is straightforward: drivers freely choose when to accept orders and are paid per delivery. Previous research shows that these jobs created opportunities for unemployed

[1] For a recent review of this literature, see Mas and Pallais (2020).

[2] Focusing on high-income countries, Machin and Meghir (2004) find that decreases low-skilled wages during the 1970s in the United Kingdom increased crime and Gould et al. (2002) show a negative relationship between the labor market prospects of unskilled American men during the 1980s-1990s and crime rates. Other work investigates whether these effects can be mediated by benefit payments (Watson et al., 2020; Foley, 2011; Khanna et al., 2023).

[3] According to Statista estimates. See the link here.

workers and raised hourly wages for those previously in other occupations. According to Callil and Picanço (2023), about one-third of delivery drivers were unemployed before joining a platform. Hourly earnings are 65% higher than in alternative jobs; on average, drivers earn 25 reais per hour, and those relying solely on delivery work make 2.5 times the monthly minimum wage. A 2022 survey of drivers reinforces this finding: earnings was the second most cited advantage, confirming the financial appeal of delivery work.[4]

This expansion represented a positive labor market shock for young, low-skilled men—the demographic most likely to commit "blue-collar" crimes such as robbery, theft, burglary, and narcotics offenses (Carmo, 2013). In 2020, 95% of drivers were male, with an average age of 29; about half had not finished high school, and only 4% had some tertiary education (Callil and Picanço, 2023). These characteristics closely mirror those of individuals typically engaged in property crime, the focus of this study. To the extent that these jobs offer an alternative source of income to this population, the introduction of iFood should reduce crime.

On the other hand, the rapid expansion of delivery work could also make crime *more* likely in certain places. Young, low-income workers who might otherwise never enter particular neighborhoods now deliver there daily. The work is highly flexible, with drivers often waiting between deliveries, and the uniform can provide cover for offenses. News reports frequently highlight crimes committed in delivery uniforms (Figure A1). This narrative has become so prominent that iFood maintains an official statement addressing it (Figure A2). Thus, anecdotal evidence suggests that the entry of iFood could increase crime in some neighborhoods, underscoring the need for empirical analysis and neighborhood-level estimates to understand how the rapid growth of delivery work affects crime.

2.2 Data

Crime Crime data come from São Paulo State's Department of Public Safety (SSP-SP) and cover all precinct-filed incident reports of larceny/theft, burglary, and robbery. Each record lists the offense type, date and time, street address, location, and geographic coordinates of the occurrence.[5] I compile all reports from 2010–2019 by cleaning and merging separate monthly, yearly, and crime-type files to build a dataset that records the total number of crimes in a municipality and year. I focus on property crime because it is the most prevalent and because data for other crimes are only available for three years. Using the universe of reports for all crime types in 2022, I find property crimes make up 98% of all reports, suggesting my dataset captures most criminal activity. The study sample ends in 2019 to exclude years affected by the COVID-19 pandemic, when consumer behavior and criminal activity were atypical.

The final dataset records 6.2 million criminal offenses over 10 years. Figure A4 shows the dispersion of crime across São Paulo municipalities. Panel A4a plots the average annual number of offenses by municipality from 2010–2019, while Panel A4b plots the average per 100,000 residents.

[4]The survey appears in Callil and Picanço (2023).

[5]About two-thirds of the observations are geocoded; I geocode 58% of the remainder using the address.

Darker shading indicates higher crime rates. The two panels look very similar, suggesting population does not explain differences in crime between municipalities.

Several factors suggest these data accurately capture patterns of criminal activity. First, victims have strong incentives to report crime: insurance companies require reports for reimbursements, and employers request them to justify absenteeism. Second, reporting costs are low, and online submission was available during the study period. Third, incident reports do not depend directly on law-enforcement quality, ensuring data consistency across neighborhoods—crucial for analyzing the spatial incidence of effects (Sections 4.2.1 and 4.2.2). The main drawback is that victimless crimes, such as drug offenses or prostitution, are not captured.

Delivery Platform Entry I use proprietary information from iFood on its expansion, including the year in which it entered each municipality. When iFood starts serving a municipality, both commercial establishments and households within the municipality are granted access to the app. The rollout began in 2012, when the first cities received its services, and continues until the present. A total of 227 municipalities had received services by 2019, indicating that they were treated during the sample period. Figure A3 displays maps of São Paulo with the municipalities served by iFood in 2012, 2014, 2016, and 2018, to illustrate the rollout.

Delivery Platform Demand I use e-receipt data for iFood purchased from Measurable AI, the largest provider of e-receipt data across emerging markets, to measure delivery demand across hours of the day and across neighborhoods. Measurable AI owns MailTime, an email productivity app which helps de-clutter mailboxes and prioritize emails with an interface formatted to imitate text-messaging. They aggregate and anonymize transactional data from the mobile devices of their app's users and translate it into data that contain information on the date and time of the transaction, the commercial establishment (pickup) address, and the geocoded delivery address. The final dataset contains about 400,000 purchases on the iFood platform over 8 years.

Municipality and Neighborhood Characteristics Information on municipality and neighborhood characteristics comes from various sources. Municipality boundary shapefiles and municipality population are retrieved from the Brazilian Institute for Geography and Statistics (IBGE), and are used to make maps of the distribution of crime across municipalities (Figure A4) and the expansion of iFood over time (Figure A3). To investigate whether the effects differ across neighborhoods with different socio-economic status, I use income data from Kummu et al. (2018) and gridded population data from the Center for International Earth Science Information Network (CIESIN, 2018).

3 Main Results

3.1 Empirical Strategy

This section investigates the effect of the introduction of flexible delivery work on crime in São Paulo state. The identification strategy compares the difference in crime before and after the introduction of iFood in municipalities that receive delivery platform services earlier versus later. The main estimating equation is:

$$\text{Crime}_{mt} = \exp\{\alpha_m + \delta_t + \beta \cdot \mathbb{1}_{mt}^{Post} + \epsilon_{mt}\}, \tag{1}$$

where the unit of observation is a municipality m in year t. Due to the staggered nature of the introduction of the delivery platform across municipalities, observations are stacked according to "treatment" timing (Goodman-Bacon, 2021). α_m and δ_t are municipality and time fixed effects, respectively. $\mathbb{1}_{mt}^{Post}$ is a binary variable that equals zero before iFood is introduced in the municipality and one after. The dependent variable is the count of criminal offenses in a municipality-year and the model is estimated using Poisson pseudo-maximum likelihood. Standard errors are clustered at the municipality level.[6]

The coefficient of interest is β, which captures the effect of the introduction of iFood on crime. The sign of β could hypothetically be positive or negative, depending on the relative strength of the forces associated with an increase in delivery jobs. Increases in total income and the opportunity cost of criminal activity should decrease crime, whereas potential increases in leisure time, the fact that a flexible job can be combined with criminal activity, and the shift in employment location as a result of delivery work are reasons crime might increase.

The identification assumption is that municipalities that receive iFood earlier and later would be on the same crime trend absent the introduction of the delivery platform. Consistent with the identification assumption, I find no indication in personal interviews with practitioners that crime or other social outcomes affected platform entry decisions, which were only concerned with the size of the potential market for their services.[7] Empirically, the lack of preexisting differences in crime between municipalities "treated" earlier and later also provides support for this assumption. Following recent recommendations in the econometrics literature on staggered difference-in-differences designs, results are also estimated using the method of Callaway and Sant'Anna (2021), which allows for heterogeneous effects across municipalities and over time.

[6]To ensure that the results are not driven by municipalities with few residents and very low crime rates, the baseline sample is restricted to municipalities with 50,000 residents or more that registered at least one offense per year during the sample period. Appendix table A1 shows that results are similar when relaxing these restrictions.

[7]Personal interviews conducted with M. Biggi, former manager at UberEats (one of iFood's main competitors during the study period), May 31st, 2023, and iFood, May 15th, 2025.

Table 1: Effect on Crime

	Dependent Variable is		
	All Crime	**Non-violent Crime**	**Violent Crime**
	(1)	(2)	(3)
	Panel A: Dependent Variable is **Count of Crime**		
Post iFood (=1)	-0.104***	-0.172***	-0.0452*
	(0.0189)	(0.0333)	(0.0238)
Dependent Variable Mean	5089	2209	2880
	Panel B: Dependent Variable is **Crime per Capita**		
Post iFood (=1)	-0.139***	-0.163***	-0.0848
	(0.0410)	(0.0375)	(0.0539)
Dependent Variable Mean	1006	498	507
Observations	1,180	1,180	1,180

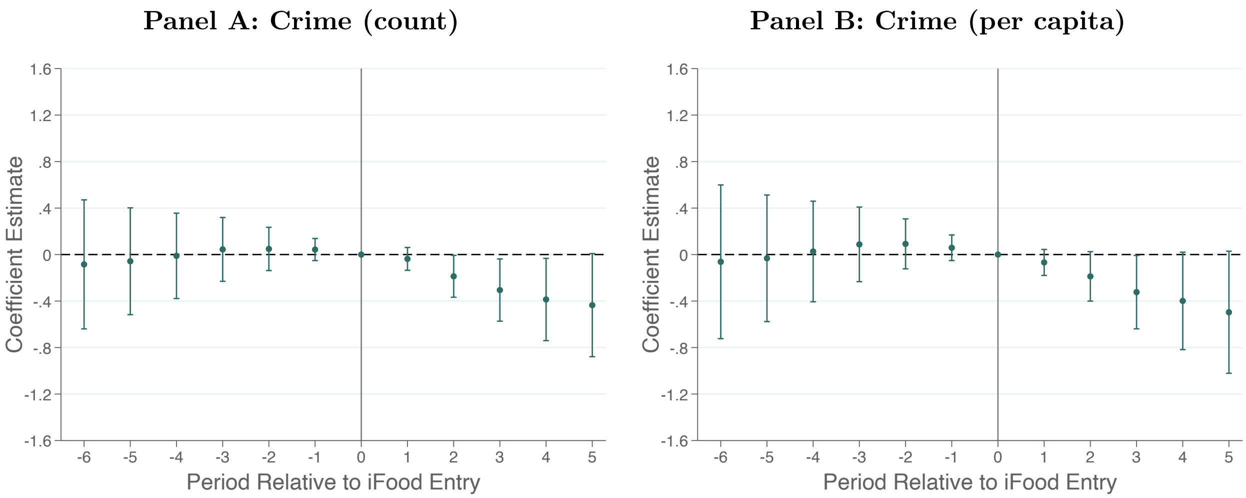
The unit of observation is a municipality–year. The sample includes all municipalities with more than 50,000 residents. All regressions are estimated by Poisson pseudo-maximum likelihood. The dependent variable is the number of criminal offenses in Panel A and the number of criminal offenses per 100,000 residents in Panel B. Column 1 includes all types of crime; columns 2 and 3 restrict to non-violent and violent offenses, respectively. "Post iFood" equals one for municipality-years after iFood is introduced in the municipality and zero otherwise. All specifications include municipality and year fixed effects. Standard errors are clustered at the municipality level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.2 Gig Work Reduces Crime

Table 1 reports the main results, estimates of Equation 1. Panel A uses the annual count of criminal offenses by municipality as the dependent variable. In column 1, the coefficient of interest is negative and statistically significant, indicating that the introduction of the delivery platform reduces property crime by 10.4% on average—equivalent to about 529 fewer crimes per municipality per year. To address the concern that crime trends might differ by market size (which in turn may be correlated with iFood's entry decision), Table A2 presents specifications that interact year fixed effects with municipality GDP, GDP per capita, and population. The estimated effect remains very similar, suggesting that differential trends by market size are not driving the results. Panel B, column 1 re-estimates the baseline specification using the number of criminal offenses per 100,000 residents as the dependent variable, to ensure that the findings are not driven by more populous municipalities with higher crime counts. The results closely match those in Panel A, with the baseline estimate implying a 13.9% decline in crime per capita.

This average negative effect could mask differences in violent and non-violent property crime. Using information from the incident reports on whether the offender used force or a weapon, columns 2 and 3 separately estimate the effects for non-violent and violent crime. I find that the effect is larger in magnitude for non-violent crime, which reduces by 17.2% ($p<0.01$), than for violent crime, which reduces by 4.5% ($p=0.06$). This pattern is consistent with the shock having a greater impact

Figure 1: Event Studies: Effect on Crime



This figure shows treatment effects over time. The regression is estimated using Poisson pseudo-maximum likelihood and the sample is all municipalities with over 50,000 residents. The sample is restricted to periods in which at least 20 municipalities are observed in both the treatment and control groups. The unit of observation is a municipality-year. The dependent variable in Panel A is the number of criminal offenses and in Panel B it is the number of criminal offenses for every 100,000 residents. Standard errors are clustered by municipality and 95% confidence intervals are reported.

on individuals at the margin of committing non-violent offenses, resulting in a larger reduction in these crimes relative to violent ones. However, in section 4.2.1 I show evidence of a large decline in violent crime in low-income neighborhoods, where the overall effect is also concentrated.

Next, I examine the dynamic effects of delivery work on crime. Figure 1 plots event studies associated with Equation 1. Panel A uses the number of offenses as the dependent variable, and Panel B uses offenses per capita.[8] Consistent with the identification assumption, there are no preexisting differences in crime between municipalities that receive iFood's services earlier versus later: the coefficients for "pre-treatment" years are indistinguishable from zero in both panels. The negative effect sets in one year after iFood is introduced and continues growing over time, reflecting the continued addition of merchants and consumers, as shown in Figure A6. Figure A7 presents results using the method outlined by Callaway and Sant'Anna (2021) to address the possibility that estimates are biased because treatment effects are heterogeneous. The estimates of the treatment effects on both crime and crime per capita from this exercise show a very similar pattern to that in Figure 1, indicating that heterogeneous treatment effects are not an important part of the story.

Geographic spillover effects The baseline estimates may understate the effect of iFood on crime if the platform's introduction also affects crime in nearby municipalities that do not themselves

[8]The main event study restricts the sample to include periods with at least 20 municipalities in both treatment and control groups. Figure A5 displays the event study with the full sample.

receive the service. There are two reasons why crime could fall in adjacent municipalities: first, some potential offenders in municipalities where gig work expands might otherwise have crossed municipal borders to commit crimes. Second, individuals living in municipalities without iFood could commute to nearby areas with the service to work as delivery drivers, benefiting from the increase in job opportunities. To test for this possibility, I estimate the effect of iFood's introduction in neighboring municipalities on crime in municipalities that do not receive iFood services during the study period. Table A3 replicates the structure of Table 1 Panel A for this sample. The point estimates are small and statistically indistinguishable from zero across columns, showing the absence of spillover effects. This is consistent with the fact that municipalities are relatively large administrative units, so cross-border commuting for work or criminal activity is uncommon.

Changes in opportunities for victimization Apart from an increase in delivery work, the decrease in crime I find could also reflect a change in consumer behavior as a result of the introduction of iFood. In particular, if the increase in availability of food delivery reduces the amount of time consumers spend outside their homes and workplaces, crime may fall due to fewer opportunities for victimization. To investigate this, Table A4 disaggregates the effect on crime by location and type of object stolen. If consumer behavior is a relevant channel, we would expect the total effect on crime to be driven by a reduction in outdoor crime that involves the theft of personal items. This is not what I find: the effect on indoor crime and outdoor crime is virtually identical (columns 1 and 2), and this is true even for crimes involving the subtraction of personal items (columns 3 and 4). In short, there is no evidence that changes in consumer behavior are driving the results.

4 Mechanisms

4.1 Opportunity Cost of Crime

Economic models of crime argue that the force responsible for the decrease in crime is the increase in the opportunity cost of criminal activity which results from positive shocks to the labor market (Becker, 1968; Ehrlich, 1996). In the context of these models, the choice between employment and crime is mutually exclusive and the opportunity cost of crime is the foregone income from the labor market. Despite the popularity of these models, there is little empirical evidence for the opportunity cost channel because large shocks to the labor market usually affect other factors that determine crime, including leisure time, mental well-being, and income (Rose, 2018).[9] This makes it impossible to isolate the effect of changes in the opportunity cost of crime from these other variables.

The fact that drivers can choose when to work and the returns to delivery work vary predictably across the day makes it possible to directly investigate the opportunity cost channel. Delivery work

[9]For example, most existing papers that investigate the effect of employment on crime leverage mass layoffs for identification, which also affect the amount of leisure time and mental well-being (e.g. Dix-Carneiro et al., 2018; Dell et al., 2019; Khanna et al., 2021).

is heavily concentrated during mealtimes because iFood is a food delivery platform. For example, about half of the delivery orders in the e-receipt data are placed between the three-hour windows around lunchtime and dinnertime, so that the returns to delivery work during these windows are larger than at other times. If the opportunity cost channel is operative, we would expect larger reductions in crime when returns to delivery work are highest. Alternatively, uniform decreases in crime across all times of the day would indicate that potential offenders are not responding to differences in the opportunity cost of crime within the day. Instead, uniform effects would be consistent with total income from delivery work being sufficient to stop drivers from offending at all times.

To test whether increases in the opportunity cost of crime are driving the main result, I separately estimate the effect of the introduction of the delivery platform for each hour of the day, exploiting time stamps in the criminal incident reports. The estimating equation is:

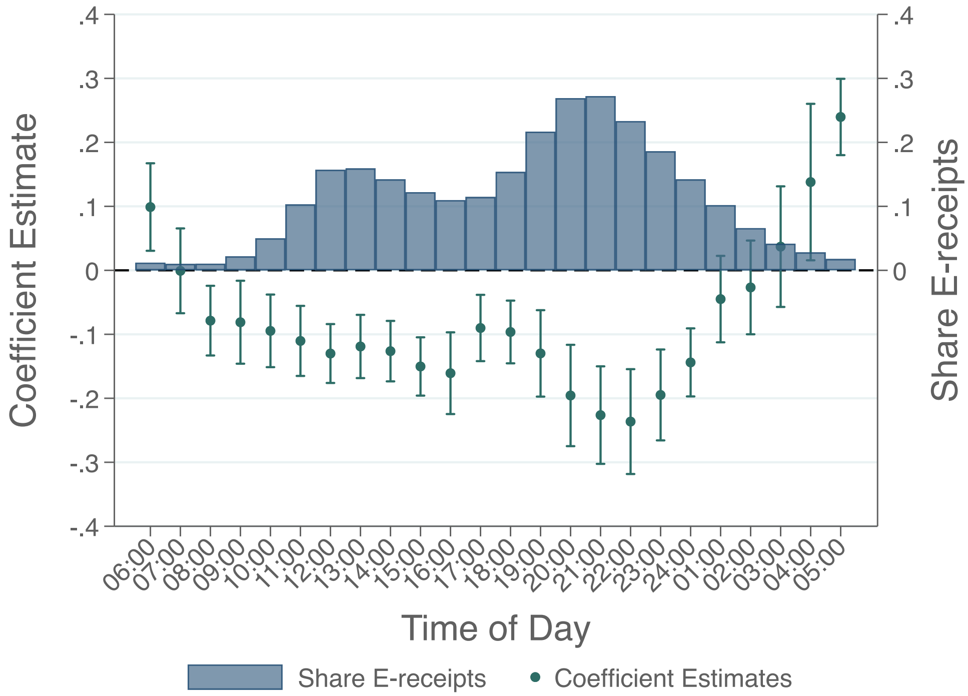
$$\text{Crime}_{hmt} = \exp\{\alpha_h + \delta_m + \phi_t + \sum_{r=1}^{24} \beta^r (\mathbb{1}_{mt}^{Post} \cdot \text{Time}_h^r) + \epsilon_{hmt}\} \tag{2}$$

The unit of observation is a time of day by municipality and year, so that $\mathbb{1}_{mt}^{Post}$ can be interacted with an indicator that equals one for each time of day, disaggregating the effect into one-hour windows. The specification controls for municipality, year, and time of day fixed effects, and standard errors are clustered at the municipality level.

Figure 2 overlays the estimates from Equation 2 on a histogram showing the share of orders in the e-receipt data made at each time of day. The histogram shows that delivery demand is almost entirely absent during early morning hours, grows steadily from 9:00 a.m. onward until it peaks during lunchtime, declines in the afternoon and peaks once more during dinnertime, when demand is greatest. The effects by time of day closely mirror fluctuations in delivery demand: the point estimates are negative and larger in magnitude at times when delivery demand is highest. The effects are *positive* from 4 to 6 a.m., when demand is lowest, indicating displacement to these hours; however, this effect represents only a handful of offenses since crime counts are very low at these times. This pattern suggests that effects are stronger when gains from work are higher. That effects are strongest when drivers are most active is also reassuring, as it is unclear *ex ante* why any omitted trend would produce this precise daily pattern of crime reduction.

Table A5 tests formally whether there are differences in crime reduction over the course of the day that vary with delivery demand. As above, the unit of observation is a time of day by municipality and year, but $\mathbb{1}_{mt}^{Post}$ is now separately interacted with four binary variables that equal one if the time of day belongs to that quartile of demand. Time of day, municipality, and year fixed effects are included, and standard errors are clustered by municipality. The dependent variable in column 1 is the count of all criminal offenses. The effect is monotonically increasing in magnitude with delivery demand, and effects are negative and significant in all but the least busy quarter of the day. This

Figure 2: Effect on Crime by Time of Day



The blue histogram plots the share of e-receipts belonging to each one-hour interval of the day. The green dots plot the coefficient estimates from a single regression. It is estimated using Poisson pseudo-maximum likelihood and the sample is all municipalities with over 50,000 residents. The unit of observation is a time of day by municipality and year. The dependent variable is the number of criminal offenses. Each dot is the coefficient on an interaction between "Post iFood" (a binary variable that equals zero before iFood is introduced and one after) and a binary variable that equals one for each time of day. The regression controls for time of day, municipality, and year fixed effects. Standard errors are clustered by municipality and 95% confidence intervals are reported.

confirms that the magnitude of the effects is increasing with the returns to delivery work.

Columns 2 and 3 estimate the specification separately for non-violent and violent crime. For non-violent crime, the effect is negative and significant across all quartiles of delivery demand (though still increasing with demand). This indicates that delivery job expansion reduces non-violent crime even when the opportunity cost is low, consistent with a broad effect of total income on criminal participation. For violent crime, by contrast, the effect is only significantly negative in the two busiest quartiles of the day. In other words, offenders refrain from violent crime only when the opportunity cost of crime is highest. Overall, these results suggest that models assuming a mutually exclusive choice between crime and employment based on the relative returns to each activity may be better suited to explain participation in more serious offenses.

To mitigate concerns that factors other than delivery demand are generating these patterns (e.g., fluctuations in the total number of crimes over the course of the day, which could be driven by many factors), I estimate an augmented version of the equation that includes binary variables for each quartile of the crime distribution interacted with the $\mathbb{1}_{mt}^{Post}$ indicator. This controls for differences in the effect across hours of the day that would be caused by factors correlated with the intensity of crime. Table A6 shows the results, which are similar to Table A5. This further supports the interpretation that crime is responding to differences in opportunity costs over the course of the day.

4.2 Spatial Distribution of Crime

4.2.1 Effects Across Neighborhood Socio-Economic Status

This section investigates whether the reduction in crime due to the introduction of iFood is equal in neighborhoods of different socio-economic status. Criminologists have documented that offenders tend to commit crime close to where they work or live, which would imply the effects should be larger in poorer neighborhoods, where delivery drivers disproportionately live and might have otherwise worked (e.g. Rengert, 2012).

To examine neighborhood-level effects, São Paulo state is divided into 0.04° × 0.04° grid cells (∼20 km^2 each). The cell size approximates the average number of neighborhoods per municipality while keeping gridded income and population aggregation feasible. I compute income per capita for each cell using gridded data from Kummu et al. (2018). Figure A8 shows São Paulo divided into grid cells and shaded by income per capita. The estimating equation is:

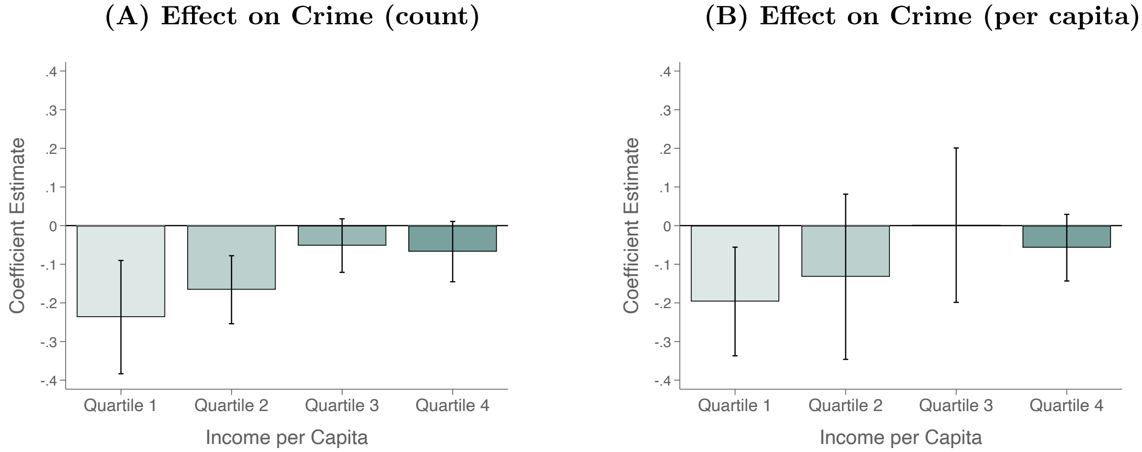
$$\text{Crime}_{\ell mt} = \exp\{\alpha_{\ell m} + \delta_t + \rho \cdot \mathbb{1}_{mt}^{Post} + \epsilon_{\ell mt}\}, \tag{3}$$

where ℓ indexes grid cells, m indexes municipality, and t indexes year. Effects are estimated separately for neighborhoods belonging to each of the four quartiles of income per capita.

Figure 3 displays the results. In Panel A, the dependent variable is the number of criminal offenses. The effect is negative for all quartiles, but is largest for the lowest-income neighborhoods. The effect in these neighborhoods is 17 percentage points larger than in the highest-income neighborhoods (p=0.045). This difference is very similar in Panel B, where the dependent variable is the count of criminal offenses per capita. This is the pattern we would expect if individuals affected by the expansion in low-skilled work are otherwise more likely to commit crime in lower-income neighborhoods. The poorest quartile of neighborhoods records roughly 50% more crime per capita than the richest quartile, which means the introduction of the delivery platform alleviates the geographic inequality in safety across neighborhoods.

Figure A9 checks whether the difference in effects across neighborhoods holds for non-violent and violent crime separately. While there is no significant difference in the effect on non-violent crime across neighborhoods, the effect on violent crime is almost entirely driven by decreases in crime in the poorest grid cells. These neighborhoods experience a 26.7% reduction in violent crime, meaning that the smaller average effect for violent crime in section 3.2 is concealing a large effect in

Figure 3: Effects by Neighborhood Income



All regressions are estimated using Poisson pseudo-maximum likelihood and the sample is all municipalities with over 50,000 residents. Each bar plots the coefficient from a separate regression. The unit of observation is a grid cell by municipality and year and the dependent variable is the number of criminal offenses in Panel A and the number of criminal offenses per 100,000 residents in Panel B. All regressions control for grid cell by municipality and year fixed effects. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

the most dangerous neighborhoods. This result reinforces the idea that the introduction of delivery work reduces inequality in exposure to crime across neighborhoods.

4.2.2 Displacement of Crime

A second possibility that might affect the spatial distribution of crime is that the introduction of the delivery platform shifts offenses toward areas where delivery drivers work (see Figure A1 for examples of this being reported by the media). This mechanism is particularly relevant in more segregated cities, where mobile delivery jobs represent a bigger change in the employment locations of low-skilled workers.

To examine this possibility, I divide São Paulo state into $0.008^\circ \times 0.008^\circ$ grid cells ($\sim$1 km^2) and use geocoded drop-off locations from e-receipt data to identify which cells recorded at least one delivery during the study period. I classify these as high delivery propensity cells. Such cells represent about 15% of all grid cells in the state and 54% of the estimation sample. I then estimate the effects of iFood's introduction separately for high- and low-propensity cells to test whether crime is displaced toward areas with greater delivery activity.

The results are reported in Table 2. Panels A and B present estimates for high- and low-delivery-propensity grid cells, respectively. Column 1 shows the effect on all crimes, while columns 2 and 3 disaggregate into non-violent and violent offenses. In Panel A, column 1, the introduction of the delivery platform reduces crime in high-propensity cells by 10.8%, an estimate nearly identical to

Table 2: Effect on Crime in Places with High and Low Delivery Propensity

	Dependent Variable is **Count of**		
	Crime	**Non-violent Crime**	**Violent Crime**
	(1)	(2)	(3)
	Panel A: High Delivery Propensity Grid Cells		
Post iFood (=1)	-0.108***	-0.188***	-0.0450
	(0.0213)	(0.0311)	(0.0307)
Dependent Variable Mean	183	80	102
Observations	21,440	21,440	21,430
	Panel B: Low Delivery Propensity Grid Cells		
Post iFood (=1)	-0.124***	-0.189***	-0.0574
	(0.0352)	(0.0340)	(0.0425)
Dependent Variable Mean	54	21	33
Observations	18,160	18,160	18,140
p-value, Panel A = Panel B	0.697	0.983	0.813

The unit of observation is a grid cell by municipality and year. All regressions are estimated using Poisson pseudo-maximum likelihood. The sample in Panel A is $1km^2$ grid cells that register at least one iFood delivery in the e-receipt data during the sample period in municipalities with over 50,000 residents. The sample in Panel B is $1km^2$ grid cells that do not register any iFood deliveries in the e-receipt data during the sample period in municipalities with over 50,000 residents. The dependent variable is the number of criminal offenses in columns 1, the number of non-violent criminal offenses in column 2, and the number of violent offenses in column 3. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after. All columns control for grid cell by municipality and year fixed effects. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

the baseline effect across all neighborhoods (10.4%, Table 1, column 1) and very similar to the effect in low-propensity cells (12.4%, Panel B, column 1). Columns 2 and 3 indicate that the effects on non-violent and violent crime are likewise very similar across high- and low-propensity cells. Table A7 repeats this analysis for the subset of high-inequality municipalities, defined by the income per capita Gini coefficient (Figure A10), where the mobility shock to workers is expected to be largest. The pattern remains: effects are statistically indistinguishable between high- and low-propensity cells. These findings suggest that the expansion of work opportunities for low-skilled workers does not lead to the relocation of crime toward new work sites.

Taken together, these results show that crime is not being systematically displaced to new locations. Instead, as shown in section 4.2.1, there appears to have been a reduction across all neighborhoods, with larger effects in lower-income areas because, absent the expansion in delivery jobs, potential offenders would disproportionately commit crime in these areas.

5 Conclusion

This paper leverages the staggered rollout of Brazil's largest food delivery platform to provide new evidence on how the expansion of gig work affects crime. I find that the introduction of the platform reduced crime rates by 10.4% on average, and that this negative effect extends to more serious crimes and persists over time. This the first study to show that expanding flexible work opportunities can generate sustained reductions in crime in a developing country, where crime rates are high and effective public safety interventions are scarce.

Turning to mechanisms, I find that reductions in crime are larger at times of day when delivery work is most lucrative, consistent with the increase in the opportunity cost of crime being an important channel. However, effects are also present at times when delivery demand is low, suggesting that the total income gain from gig work also drives crime down. In addition, the spatial incidence of the effect is not even: reductions are largest in lower-income neighborhoods, where delivery drivers disproportionately live. At the same time, there is no evidence that crime is displaced toward high-income neighborhoods or areas with greater delivery demand, even in municipalities where segregation is most pronounced.

Delivery work has potential synergies with crime—by increasing free time, mobility, and opportunities for concealment—that would predict the opposite effect. Instead, I find a sizable, persistent reduction in crime. These findings may extend to other forms of flexible work, which are growing worldwide and were accelerated by the COVID-19 pandemic. Moreover, the results on mechanisms suggest that aligning financial alternatives with periods of high crime could maximize their impact, and that linking low-skilled workers to jobs in wealthier areas may reduce crime and narrow gaps in neighborhood safety without displacing offenses.

References

Angrist, Joshua D, Sydnee Caldwell, and Jonathan V Hall, "Uber versus taxi: A driver's eye view," *American Economic Journal: Applied Economics*, 2021, *13* (3), 272–308.

Becker, Gary S, "Crime and punishment: An economic approach," *Journal of political economy*, 1968, *76* (2), 169–217.

Bellégo, Christophe and Joeffrey Drouard, "Fighting Crime in Lawless Areas: Evidence from Slums in Rio de Janeiro," *American Economic Journal: Economic Policy*, 2024, *16* (1), 124–159.

Blattman, Christopher, Donald P Green, Daniel Ortega, and Santiago Tobón, "Place-based interventions at scale: The direct and spillover effects of policing and city services on crime," *Journal of the European Economic Association*, 2021, *19* (4), 2022–2051.

_ , Gustavo Duncan, Benjamin Lessing, and Santiago Tobon, "Statebuilding in the city: An experiment in civilian alternatives to policing," Technical Report, Center for Open Science 2022.

Britto, Diogo GC, Paolo Pinotti, and Breno Sampaio, "The effect of job loss and unemployment insurance on crime in Brazil," *Econometrica*, 2022, *90* (4), 1393–1423.

Callaway, Brantly and Pedro HC Sant'Anna, "Difference-in-differences with multiple time periods," *Journal of econometrics*, 2021, *225* (2), 200–230.

Callil, Victor and Monise Picanço, "Mobilidade Urbana e Logística de Entregas: Um Panorama Sobre o Trabalho de Motoristas e Entregadores Com Aplicativos," 2023.

Carmo, Carlos Roberto Souza, "Demografia e Criminalidade: um estudo baseado em métodos quantitativos aplicados a "crimes de rua"," *Revista Ciências Humanas*, 2013, *6* (2).

Chen, M Keith, Peter E Rossi, Judith A Chevalier, and Emily Oehlsen, "The value of flexible work: Evidence from Uber drivers," *Journal of political economy*, 2019, *127* (6), 2735–2794.

CIESIN, "Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 11," 2018.

Cook, Cody, Rebecca Diamond, Jonathan V Hall, John A List, and Paul Oyer, "The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers," *The Review of Economic Studies*, 2021, *88* (5), 2210–2238.

Dahl, Gordon and Stefano DellaVigna, "Does movie violence increase violent crime?," *The quarterly journal of economics*, 2009, *124* (2), 677–734.

Dell, Melissa, Benjamin Feigenberg, and Kensuke Teshima, "The violent consequences of trade-induced worker displacement in mexico," *American Economic Review: Insights*, 2019, *1* (1), 43–58.

Dix-Carneiro, Rafael, Rodrigo R Soares, and Gabriel Ulyssea, "Economic shocks and crime: Evidence from the brazilian trade liberalization," *American Economic Journal: Applied Economics*, 2018, *10* (4), 158–195.

Egger, Eva-Maria, "Internal migration and crime in Brazil," *Economic Development and Cultural Change*, 2022, *71* (1), 223–259.

Ehrlich, Isaac, "Crime, punishment, and the market for offenses," *Journal of economic perspectives*, 1996, *10* (1), 43–67.

Foley, C Fritz, "Welfare payments and crime," *The review of Economics and Statistics*, 2011, *93* (1), 97–112.

Glaeser, Edward L, Bruce Sacerdote, and Jose A Scheinkman, "Crime and social interactions," *The Quarterly journal of economics*, 1996, *111* (2), 507–548.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Gould, Eric D, Bruce A Weinberg, and David B Mustard, "Crime rates and local labor market opportunities in the United States: 1979–1997," *Review of Economics and statistics*, 2002, *84* (1), 45–61.

Guerra, Julia, Joana Monteiro, and Vinicius Pecanha, "Crime prevention through urban requalification and municipal police presence," *Economics Letters*, 2025, p. 112448.

Haddad, Eduardo, Renato Vieira, Fernando Perobelli, and de Araújo Inácio, "Impacto Socioeconômico do iFood," Technical Report, Fundação Instituto de Pesquisas Econômicas 2023.

IADB, *Closing Knowledge Gaps: Toward Evidence-Based Crime Prevention Policies in Latin America and the Caribbean*, Inter-American Development Bank, 2015.

IPA, "Evidence in Crime and Violence in Latin America and the Caribbean," Technical Report, Innovations for Poverty Action 2021.

IPEA, "Painel da Gig Economy no setor de transportes do Brasil: quem, onde, quantos e quanto ganham," Technical Report, Instituto de Pesquisa Econômica Aplicada (IPEA) Junho 2022. Accessed: 2024-03-10.

Jacob, Brian A and Lars Lefgren, "Are idle hands the devil's workshop? Incapacitation, concentration, and juvenile crime," *American economic review*, 2003, *93* (5), 1560–1577.

Khanna, Gaurav, Carlos Medina, Anant Nyshadham, Christian Posso, and Jorge Tamayo, "Job loss, credit, and crime in Colombia," *American Economic Review: Insights*, 2021, *3* (1), 97–114.

_ , _ , _ , Daniel Ramos, Jorge Tamayo, and Audrey Tiew, "Spatial mobility, economic opportunity, and crime," *Preliminary Draft*, 2022.

_ , _ , _ , Jorge Tamayo, and Nicolas Torres, "Formal Employment and Organised Crime: Regression Discontinuity Evidence from Colombia," *The Economic Journal*, 2023, *133* (654), 2427–2448.

Kummu, Matti, Maija Taka, and Joseph HA Guillaume, "Gridded global datasets for gross domestic product and Human Development Index over 1990–2015," *Scientific data*, 2018, *5* (1), 1–15.

Lafrogne-Joussier, Raphael and Vincent Rollet, "Ambient Density and Urban Crime: Evidence from Smartphone Data," *Available at SSRN 4440554*, 2023.

Machin, Stephen and Costas Meghir, "Crime and economic incentives," *Journal of Human resources*, 2004, *39* (4), 958–979.

Mancha, Andre, Michael Weintraub, and Joana Monteiro, "A New Path to Police Reform? Effects of a New Police Squad in Ceará, Brazil," *Effects of a New Police Squad in Ceará, Brazil (July 25, 2025)*, 2025.

Mas, Alexandre and Amanda Pallais, "Alternative work arrangements," *Annual Review of Economics*, 2020, *12*, 631–658.

Mejia, Daniel and Pascual Restrepo, "Bushes and bullets: Illegal cocaine markets and violence in Colombia," *Documento CEDE*, 2013, (2013-53).

Monteiro, Joana, Eduardo Fagundes, and Julia Guerra, "Letalidade policial e criminalidade violenta," *Revista de Administração Pública*, 2020, *54*, 1772–1783.

Papp, Anna, "Who Bears Climate Change Damages? Evidence from the Gig Economy," 2024. Job Market Paper, Columbia University, School of International and Public Affairs.

Pezzuchi, Gastón, Eduardo Fagundes, Rodrigo Serrano-Berthert, Claudio Todisco, Carolina Zancan, Franck Cione, and Reginaldo Santa Rosa, "An Experimental Evaluation of Hot Spot Policing in Brazil," 2024. Working paper.

Plotkin, P, "Dinner at Your Door: How Delivery Platforms Affect Workers and Firms," Technical Report, Working paper. 2, 4 2024.

Rengert, George F, "The journey to crime," in "Punishment, places and perpetrators," Willan, 2012, pp. 169–181.

Rose, Evan K, "The effects of job loss on crime: evidence from administrative data," *Available at SSRN 2991317*, 2018.

Scarelli, Thiago, "Workers' Preferences over Payment Schedules: Evidence from Ridesharing Drivers," *Working Paper*, 2024.

Sviatschi, Maria Micaela, "Making a narco: Childhood exposure to illegal labor markets and criminal life paths," *Econometrica*, 2022, *90* (4), 1835–1878.

Watson, Brett, Mouhcine Guettabi, and Matthew Reimer, "Universal cash and crime," *Review of Economics and Statistics*, 2020, *102* (4), 678–689.

Appendix Figures and Tables

Figure A1: News Articles Reporting on Delivery Drivers Committing Crime

Falso entregador de aplicativo é preso menos de dois meses após sair da cadeia e voltar a assaltar no Rio

Homem usava roupas e mochila de entregador para praticar assaltos, segundo a polícia. Ele é suspeito de balear um cliente de uma barbearia no final de janeiro, na Tijuca, durante um assalto.

Por Alice Portes, Henrique Coelho, TV Globo e g1 Rio
02/02/2024 09h26 · Atualizado há uma semana

São Paulo

Vídeos flagram assaltos de falsos entregadores em bairros ricos de SP

Em meio à alta de roubos em bairros ricos de SP, vídeos de câmeras de segurança mostram assaltos de falsos entregadores de delivery

Felipe Resk
20/01/2024 05:15, atualizado 20/01/2024 10:30

This figure shows news stories from 2024 about people using iFood uniforms as disguises to commit crime. The first headline translates to "Fake app deliveryman is arrested less than two months after leaving prison in Rio." The second headline translates to "Videos capture robberies by fake deliverymen in wealthy neighborhoods of São Paulo."

Figure A2: iFood Blog Post on Delivery Drivers and Crime

27/04/2022 | Delivery drivers, Releases

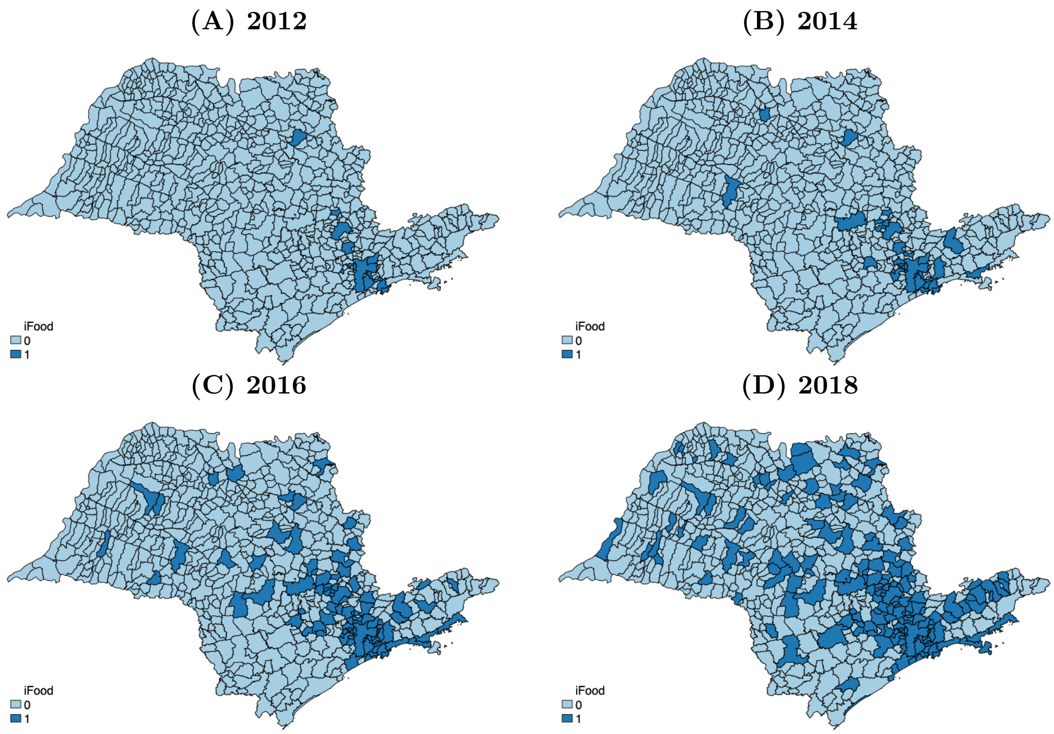
Position on crimes committed by people using iFood bags

Comunicado

ifood news

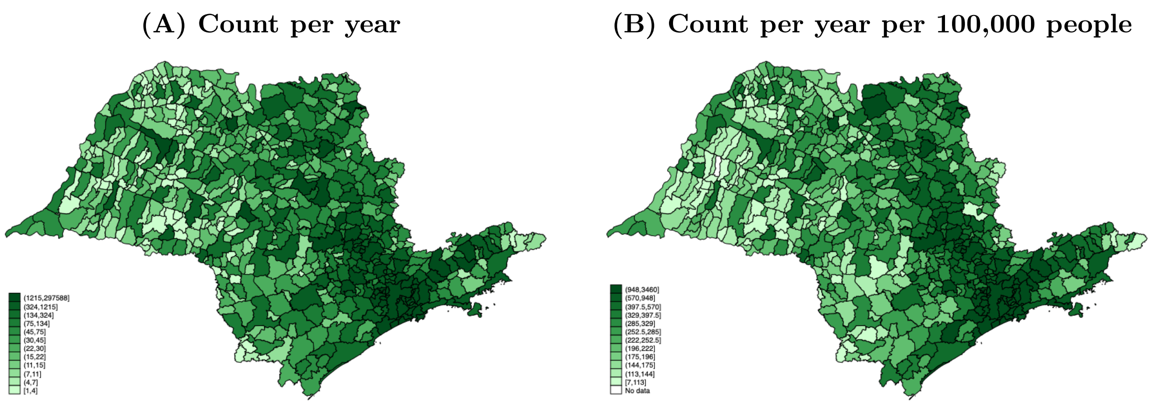
This figure shows a screenshot of a blog post published by iFood in 2022 describing the steps it takes to mitigate crime committed by delivery drivers. The blog post can be found under this link.

Figure A3: Rollout of iFood Over Time



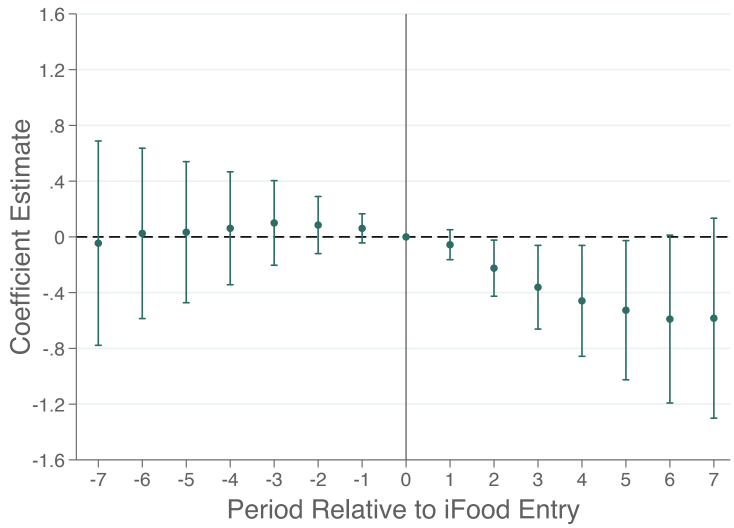
This figure shows the municipalities that have iFood services in 2012 (Panel A), 2014 (Panel B), 2016 (Panel C), and 2018 (Panel D).

Figure A4: Crime Across Municipalities in São Paulo



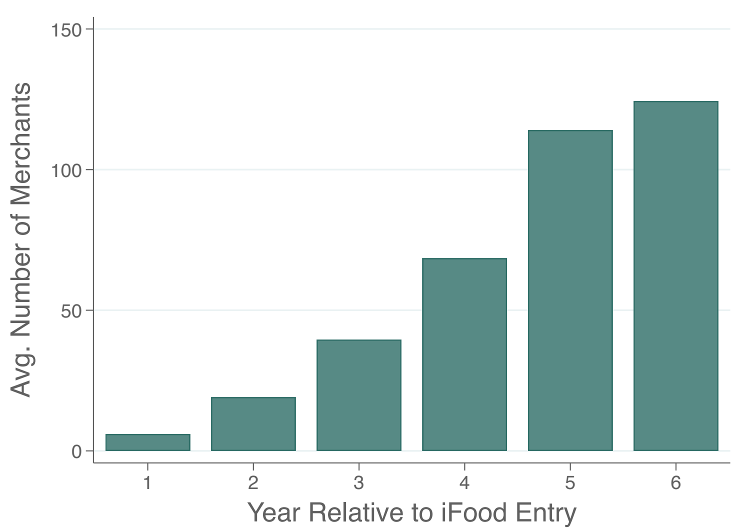
This figure shows the distribution of crime across municipalities in the state of São Paulo. In Panel A, municipalities are shaded according to the average count of criminal offenses registered by precincts per year from 2010 to 2019. In Panel B, municipalities are shaded according to the average count of criminal offenses per 100,000 people per year registered by precincts from 2010 to 2019.

Figure A5: Event Study without Trimming



This figure shows dynamic treatment effects over time. The regression is estimated using Poisson pseudo-maximum likelihood and the sample is all municipalities with over 50,000 residents. The unit of observation is a municipality-year. The dependent variable is the number of criminal offenses. Standard errors are clustered by municipality and 95% confidence intervals are shown.

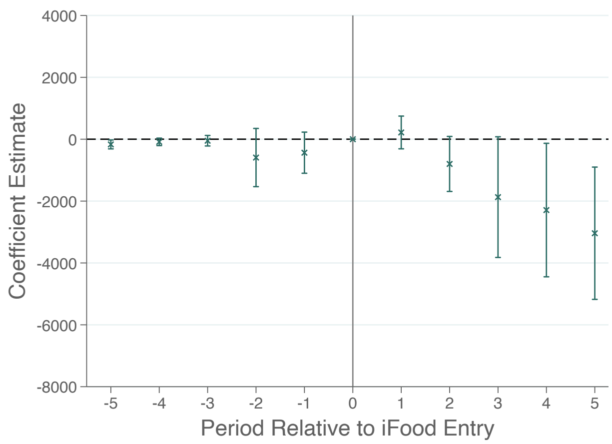
Figure A6: Number of Merchants Registered with iFood Over Time



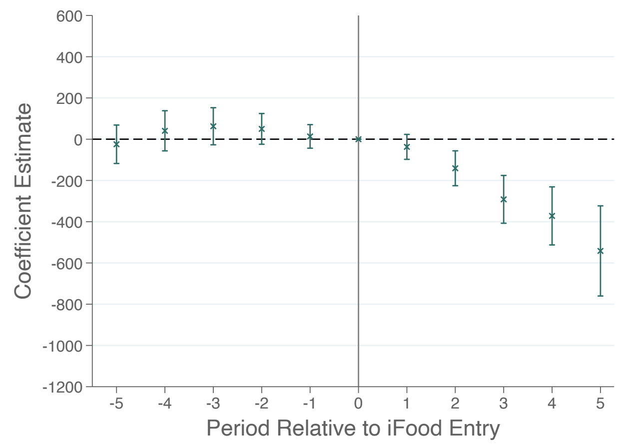
This figure displays the average number of merchants (commercial establishments) per 100,000 residents registered with iFood in each municipality over time.

Figure A7: Event Studies Accounting for Staggered Rollout

Panel A: Crime (count)

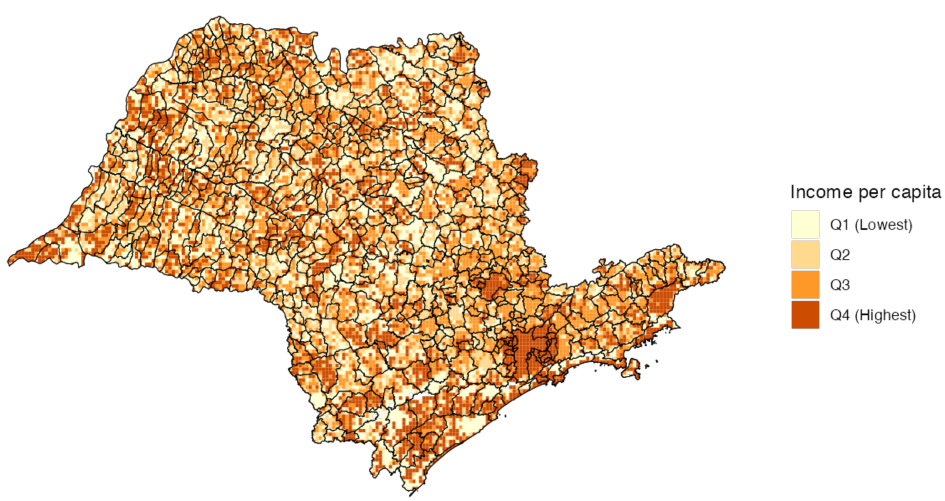


Panel B: Crime (per capita)



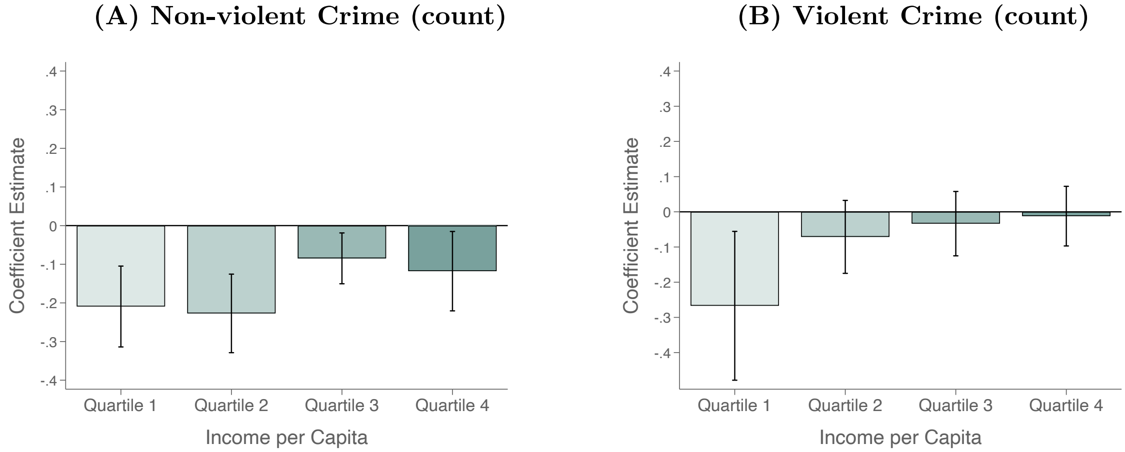
This figure shows treatment effects over time estimated using the method outlined in Callaway and Sant'Anna (2021). The sample is all ever-treated municipalities with over 50,000 residents, and is restricted to periods in which at least 20 municipalities are observed in both the treatment and control groups. The unit of observation is a municipality-year. The dependent variable is the number of criminal offenses in Panel A and the number of criminal offenses per 100,000 residents in Panel B. Standard errors are clustered by municipality and 95% confidence intervals are shown.

Figure A8: São Paulo State Shaded by Income per Capita



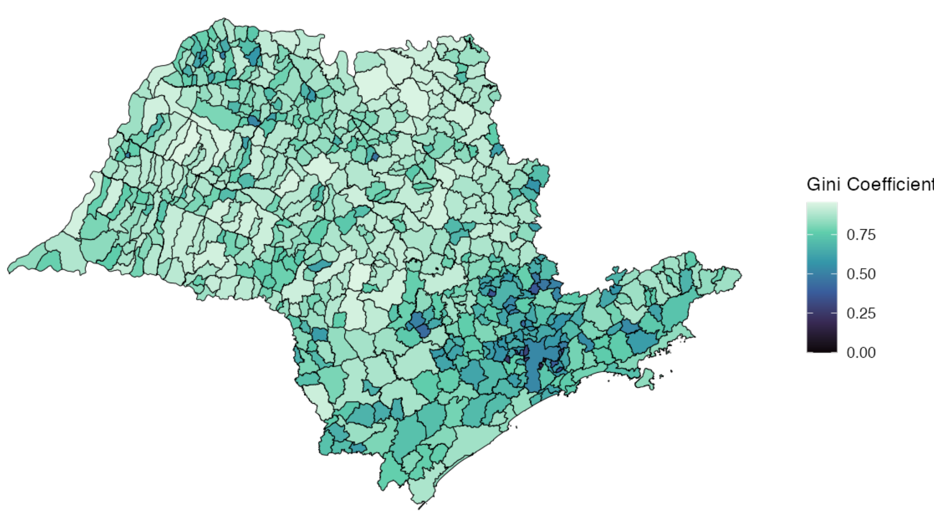
This figure shows a map of São Paulo state divided into $0.04^\circ \times 0.04^\circ$ grid cells and shaded according to quartiles of income per capita. Darker shades represent higher-income grid cells.

Figure A9: Effects by Neighborhood Income and Type of Offense



All regressions are estimated using Poisson pseudo-maximum likelihood and the sample is all municipalities with over 50,000 residents. Each bar plots the coefficient from a separate regression. The unit of observation is a grid cell by municipality and year and the dependent variable is the number of non-violent criminal offenses in Panel A and the number of violent offenses in Panel B. All regressions control for grid cell by municipality and year fixed effects. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure A10: São Paulo State Shaded by Gini Coefficient



This figure shows a map of São Paulo state with municipalities shaded by their Gini coefficient, calculated from the income distribution of 0.04° × 0.04° grid cells within each municipality. Lighter shades indicate higher Gini coefficients and greater income inequality.

Table A1: Effect on Crime: Relaxing Population Restriction

	Dependent Variable is **Count of**		
	All Crime	**Non-violent Crime**	**Violent Crime**
	(1)	(2)	(3)
Post iFood (=1)	-0.233***	-0.325***	-0.138***
	(0.0241)	(0.0258)	(0.0295)
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Dependent Variable Mean	969	428	580
Observations	6,440	6,440	6,440

The unit of observation is a municipality-year and the sample is all municipalities. All regressions are estimated using Poisson pseudo-maximum likelihood. The dependent variable is the number of criminal offenses in column 1, the number of non-violent offenses in column 2, and the number of violent offenses in column 3. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A2: Effect on Crime: Controlling for Differential Trends by Market Size

	Dependent Variable is **Count of Crime**			
	(1)	(2)	(3)	(4)
Post iFood (=1)	-0.104***	-0.0877***	-0.113***	-0.103***
	(0.0189)	(0.0263)	(0.0272)	(0.0258)
Municipality Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes	-	-	-
Year FE X Pre-period Municipality GDP	-	yes	yes	yes
Year FE X Pre-period Municipality GDP per Capita	-	-	yes	yes
Year FE X Population	-	-	-	yes
Dependent Variable Mean	5089	5089	5089	5089
Observations	1,180	1,180	1,180	1,180

The unit of observation is a municipality-year and the sample is all municipalities with more than 50,000 residents. All regressions are estimated using Poisson pseudo-maximum likelihood. The dependent variable is the number of criminal offenses. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after. Column 1 controls for municipality and year fixed effects. Columns 2, 3, and 4 additionally control for year fixed effects interacted with municipality GDP, year fixed effects interacted with municipality GDP per capita, and year fixed effects interacted with population, respectively. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A3: Spillover Effects on Crime in Neighboring Municipalities

	Dependent Variable is **Count of**		
	All Crime	**Non-violent Crime**	**Violent Crime**
	(1)	(2)	(3)
Neighbor's Post iFood (=1)	0.0310	0.0370	-0.0170
	(0.0727)	(0.0580)	(0.138)
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Dependent Variable Mean	21	15	7
Observations	3,960	3,960	3,960

The unit of observation is a municipality-year. The sample is all municipalities that *did not* receive iFood services during the study period (2010-2019). All regressions are estimated using Poisson pseudo-maximum likelihood. The dependent variable is the number of criminal offenses in column 1, the number of non-violent offenses in column 2, and the number of violent offenses in column 3. "Neighbor's Post iFood" is a binary variable that equals 0 before iFood is introduced in any municipality bordering those in the sample, and 1 once at least one neighboring municipality begins receiving iFood services. All columns control for municipality and year fixed effects. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Effects on Crime by Location and Type of Item Stolen

	Dependent Variable is **Crime (count)**			
	Any Item, Indoors	**Any Item, Outdoors**	**Personal Item, Indoors**	**Personal Item, Outdoors**
	(1)	(2)	(3)	(4)
Post iFood (=1)	-0.144***	-0.169***	-0.141***	-0.155***
	(0.0318)	(0.0266)	(0.0332)	(0.0306)
Municipality Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Dependent Variable Mean	858	3288	592	1495
Observations	1,180	1,180	1,180	1,180

The unit of observation is a municipality-year. The sample is all municipalities with over 50,000 residents. All regressions are estimated using Poisson pseudo-maximum likelihood. In column 1, the dependent variable is the number of criminal offenses committed indoors, and in column 2, it is the number committed outdoors. Columns 3 and 4 focus specifically on offenses involving the theft of a personal item, with column 3 showing those committed indoors and column 4 those committed outdoors. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after. All columns control for municipality and year fixed effects. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Effect by Quartiles of Delivery Demand

	Dependent Variable is **Count of**		
	Crime	**Non-violent Crime**	**Violent Crime**
	(1)	(2)	(3)
1st Quartile Delivery Demand X Post iFood (=1)	0.0438*	-0.0757**	0.0981***
	(0.0262)	(0.0358)	(0.0357)
2nd Quartile Delivery Demand X Post iFood (=1)	-0.0877***	-0.154***	-0.0352
	(0.0295)	(0.0434)	(0.0400)
3rd Quartile Delivery Demand X Post iFood (=1)	-0.121***	-0.149***	-0.0917***
	(0.0216)	(0.0367)	(0.0254)
4th Quartile Delivery Demand X Post iFood (=1)	-0.191***	-0.229***	-0.167***
	(0.0350)	(0.0377)	(0.0322)
p-value, Q1=Q4	< 0.001	< 0.001	< 0.001
Dependent Variable Mean	167	46	120
Observations	26,160	26,160	26,160

All regressions are estimated using Poisson pseudo-maximum likelihood and the sample is all municipalities with over 50,000 residents. The unit of observation is a time of day by municipality and year. The dependent variable is the number of criminal offenses in column 1, the number of non-violent offenses in column 2, and the number of violent offenses in column 3. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after. It is interacted with binary variables that equal one when the time of day belongs to that quartile of delivery demand. All columns control for time of day, municipality, and year fixed effects. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A6: Effect by Quartiles of Delivery Demand Controlling for Crime Level

	Dependent Variable is **Count of**		
	Crime	**Non-violent Crime**	**Violent Crime**
	(1)	(2)	(3)
1st Quartile Delivery Demand X Post iFood (=1)	0.00370	-0.103***	0.0434
	(0.0247)	(0.0302)	(0.0328)
2nd Quartile Delivery Demand X Post iFood (=1)	-0.137***	-0.146***	-0.115***
	(0.0251)	(0.0299)	(0.0348)
3rd Quartile Delivery Demand X Post iFood (=1)	-0.147***	-0.122***	-0.145***
	(0.0232)	(0.0260)	(0.0267)
4th Quartile Delivery Demand X Post iFood (=1)	-0.192***	-0.235***	-0.168***
	(0.0354)	(0.0361)	(0.0323)
p-value, Q1=Q4	< 0.001	< 0.001	< 0.001
Dependent Variable Mean	167	46	120
Observations	26,160	26,160	26,160

All regressions are estimated using Poisson pseudo-maximum likelihood and the sample is all municipalities with over 50,000 residents. The unit of observation is a time of day by municipality and year. The dependent variable is the number of criminal offenses in column 1, the number of non-violent offenses in column 2, and the number of violent offenses in column 3. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after. It is interacted with binary variables that equal one when the time of day belongs to that quartile of delivery demand. All columns also control for the "Post iFood" indicator interacted with binary variables that equal one if the time of day belongs to that quartile of crime (not shown), as well as time of day, municipality, and year fixed effects. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A7: Effects in High and Low Delivery Propensity Locations in Unequal Municipalities

	Dependent Variable is **Count of**		
	Crime	**Non-violent Crime**	**Violent Crime**
	(1)	(2)	(3)
	Panel A: High Delivery Propensity Grid Cells		
Post iFood (=1)	-0.142***	-0.170***	-0.124**
	(0.0479)	(0.0415)	(0.0598)
Dependent Variable Mean	68	38	30
Observations	7,590	7,590	7,580
	Panel B: Low Delivery Propensity Grid Cells		
Post iFood (=1)	-0.202***	-0.225***	-0.126*
	(0.0470)	(0.0490)	(0.0662)
Dependent Variable Mean	33	18	15
Observations	9,500	9,500	9,480
p-value , Panel A = Panel B	0.371	0.392	0.982

The unit of observation is a grid cell by municipality and year. All regressions are estimated using Poisson pseudo-maximum likelihood and consider only municipalities with above median inequality as measured by the Gini coefficent (see Figure A10). The sample in Panel A is $1km^2$ grid cells that register at least one iFood delivery in the e-receipt data during the sample period in municipalities with over 50,000 residents. The sample in Panel B is $1km^2$ grid cells that do not register any iFood deliveries in the e-receipt data during the sample period in municipalities with over 50,000 residents. The dependent variable is the number of criminal offenses in columns 1, the number of non-violent criminal offenses in column 2, and the number of violent offenses in column 3. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after. All columns control for grid cell by municipality and year fixed effects. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.