The Gig Economy and Crime in Brazil*

Isadora A. Frankenthal

May 2025

Abstract

This study investigates how the expansion of gig work affects the level and geographic distribution of crime, leveraging the rapid expansion of the largest food delivery platform in Brazil (iFood). While a positive labor market shock should increase the opportunity cost of crime, greater work flexibility makes it easier to shift back and forth between criminal activity and employment. Moreover, by hiring low-skilled workers to deliver goods in high-income neighborhoods, gig work could alter the spatial incidence of criminal activity. Exploiting the staggered rollout of iFood alongside the universe of geo-coded criminal incident reports from São Paulo state, I find that the rise in gig work reduced crime, including violent crime, and that this effect persisted over time. The effect is larger in magnitude at times when the returns to delivery work are highest and in lower-income neighborhoods, where delivery workers tend to reside. I find no evidence that delivery work transported crime to places with high delivery demand.

*I am very thankful to Daron Acemoglu, Nikhil Agarwal, David Atkin, Abhijit Banerjee, Esther Duflo, Amy Finkelstein, Simon Jäger, Horacio Larreguy, Joana Monteiro, Jacob Moscona, Ben Olken, 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, Marina Merlo, and Debora Gershon for their help with the iFood rollout 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). Moreover, the growth of delivery jobs was a positive labor market shock to young and unskilled men, the population most likely to commit "blue-collar" crime. From this perspective, the dramatic rise of gig work may have precipitated a large reduction in crime. On the other hand, however, the flexibility of gig work means employment can be more easily combined with criminal activity and that overall free time may increase, raising overall crime rates (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.[1] 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 expansion of the largest food delivery platform in Brazil (iFood) across municipalities in São Paulo, the most populous state in the country, to investigate how the expansion of delivery platform work affects the level and geographic distribution of crime. The state of São Paulo is home to numerous large cities with high crime rates and strong demand for delivery services, making it an ideal setting to study how the expansion of gig work affects crime in developing regions. In addition, the availability of reliable, precinct-level geocoded and time-stamped crime data allows me to study the impact of gig work on crime and identify the channels underpinning the effect.

Combining ten years of data on property crime 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%. This is equivalent to 529 fewer offenses per municipality and year on average. This negative effect extends

[1] In fact, it is common to see anecdotes in the news about individuals using delivery uniforms as cover for committing crime (Figure A1). Instances like this are so recurrent in the news that iFood put out a blog post in 2022 describing steps they take to try and mitigate the problem. Figure A2 shows a screenshot of the blog post (linked here).

to violent property crime, when there is use of force or a weapon, and persists up to five years after the delivery platform is introduced. The effect size 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). iFood deliveries are concentrated around mealtimes, meaning that the returns to work (and therefore the opportunity cost of crime) vary predictably across the day. Combined with information on the exact time each offense was committed, this fact allows me to look for evidence of the opportunity cost channel. To do this, I disaggregate the main effect by time of day. If the increase in the opportunity cost of crime is driving the main results, effects should be stronger at times when returns to delivery work are higher. I find that effects are significantly stronger when delivery demand is highest, and that this is particularly true for violent crime. However, effects are also present when delivery demand is low, consistent with an effect of total income on criminal participation.

I then use the geo-coded 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. Moreover, I find no evidence of a corresponding increase in crime in high-income neighborhoods, inconsistent with anecdotal accounts from the Brazilian media (see Figure A1). 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 no evidence of crime shifting toward streets that demand delivery services: the estimated effect is virtually identical to the main result, including in municipalities with above-median income inequality where segregation is most pronounced.

Related Literature This project contributes to past work examining the economic impacts of gig work.[2] For example, using data on hourly earnings and driving, Chen et al. (2019) show that drivers

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

employed by ride-hailing apps value the real-time flexibility of the job. Additionally, randomized interventions by Scarelli (2024) and Angrist et al. (2021) document that workers in ride-hailing apps value being paid in real-time and not having to lease the car, as they do in the traditional taxi market. Moreover, Cook et al. (2021) find that job flexibility provided by gig work favors women and that the pay gap between men and women employed by digital platforms is closed once you account for other differences across genders. 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.[3] This paper extends this evidence by examining the market-level effect of a large shock to flexible jobs, which has 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 Brazil's persistently high crime rates and the effects of public policies aimed at reducing them (e.g., Monteiro et al., 2020; Egger, 2022; Pezzuchi et al., 2024; Guerra et al., 2025; Mancha et al., 2025). Most policies that reduce crime rely on increasing police presence or pacifying gang-controlled territories, but these strategies are costly and often either displace crime to other areas or backfire (see Bellégo and Drouard, 2024). The finding that gig work 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 delivery platform rollout 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 Introduction and Expansion of iFood

iFood introduced its delivery platform in 2012, when it was the first of its kind in Brazil. It has grown rapidly since then. It currently has approximately 63 million users and owns 87% of the

[3] 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).

food delivery platform market in Brazil.[4] This market share is so significant that it is currently the subject of multiple investigations by Brazil's Administrative Council for Economic Defense (CADE), the government agency that regulates national competition.[5] According to a report by the company, iFood employed 537,964 delivery drivers in 2020, which is approximately 0.5% of the entire Brazilian workforce (Haddad et al., 2023). It is straightforward to register as a driver: the individual needs to download the iFood driver app, fill in some forms and provide a photograph of a government-issued identification document and bank account information. The drivers are completely free to choose when to be actively accepting orders to deliver, and are paid by delivery.

Previous studies have documented that delivery platform jobs provided job opportunities for unemployed workers and raised the hourly wages of workers who were previously in different occupations. According to a report by Callil and Picanço (2023), about a third of all delivery drivers in Brazil were unemployed before working for one of the delivery apps. Moreover, the earnings per hour of delivery drivers are 65% higher than earnings in other jobs they might have otherwise performed. On average, drivers earn 25 Brazilian reais (roughly 5 US dollars) per hour and drivers who rely solely on delivery work as a source of income make 2.5 times the monthly minimum wage. A survey conducted in 2022 that asked delivery drivers what job characteristics they most valued describes qualitative evidence that supports this finding. Earnings was the second most cited advantage, confirming that delivery work is a financially attractive job.[6]

The individuals who work for iFood as delivery drivers are generally young, low-skilled men, which is the population most likely to commit "blue collar" crime (Carmo, 2013). These are crimes that are small in scale and committed for immediate financial gain to the individual, such as robbery, theft, burglary, and narcotic production or distribution. In 2020, 95% of all delivery drivers were male, with an average age of 29 years. About half of the drivers had not completed high school, and only 4% had some kind of tertiary education (Callil and Picanço, 2023). These coincide with the demographic characteristics of individuals who tend to commit property crime, the focus of this study, who are almost always young, male, and relatively uneducated (Carmo, 2013).

Although the expansion in delivery jobs was a positive labor market shock, there is reason to believe that the rapid expansion of delivery work could make crime *more* likely in high-delivery locations. Many Brazilian cities are so spatially segregated that delivery drivers might otherwise never visit certain neighborhoods, yet now they deliver there daily. Delivery work itself is highly flexible, with drivers often waiting stretches of time between deliveries, and the delivery uniform can provide a form of cover for committing offenses. In fact, it is extremely common to see news stories about individuals using delivery uniforms while committing crimes (Figure A1). This problem has become so visible that iFood keeps an official statement addressing it on their website (Figure A2). It is unclear, however, whether crime is truly increasing because delivery work makes offending easier,

[4] According to estimates by Statista, a global data and business intelligence platform. See the link here.
[5] As reported by CADE's website, linked here.
[6] The results of this survey appear in the paper by Callil and Picanço (2023), cited above.

or if these offenses would have happened anyway and the delivery uniform is simply a new way to conceal them. This ambiguity underscores the need to turn to data to understand the impact of the rapid growth of delivery work on crime.

2.2 Data

Crime Data on crime come from São Paulo State's Department of Public Safety.[7] These data record all criminal incident reports filed in any precinct in the State of São Paulo. The data include information on the type of crime, the precinct where the crime was registered, the date and time of the occurrence, and the address and coordinates of the occurrence. I clean and compile all property crime reports from 2010 to 2019 from separate files containing the incident reports for each month, year, and type of crime, to build a dataset that records the total number of property crimes per municipality and year. I focus on property crime both because this is the most relevant type of criminal activity and because data on other forms of crime are only publicly available for three years and are incomplete. However, using the universe of criminal incident reports for all types of crime available in 2022, I find incidents classified as property crime make up 98% of all criminal incident reports, suggesting that the data I compile covers a large share of overall criminal activity. The study sample stops in 2019 to exclude years that were affected by the Covid-19 pandemic, when consumer behavior and criminal activity were atypical.[8]

There are several reasons why these data are likely to accurately capture patterns of criminal activity. First, victims have strong incentives to report crime. Insurance companies require incident reports in order to issue reimbursements and employers ask for reports to justify employee absenteeism. Second, reporting costs are low, and submitting an incident report online is an option during the study period. Third, incident reports do not directly depend on the quality of law enforcement. This ensures the quality of the data doesn't vary across neighborhoods, which is crucial for the analysis of spatial incidence of the effect (Sections 4.2.1 and 4.2.2). The main downside of data from incident reports is that they miss victimless crimes, such as drug offenses or prostitution.[9]

The final dataset records 6.2 million criminal offenses over 10 years. Figure A3 illustrates the dispersion of crime across municipalities in São Paulo. Panel A3a shows the average number of criminal offenses by municipality and year from 2010 to 2019, while Panel A3b shows the average number of criminal offenses by municipality and year for every 100,000 residents of the municipality. The darker shaded municipalities have higher crime rates. The most dangerous municipalities are in the Southeast, around the city of São Paulo, whereas the safest municipalities are scattered around the Northwest of the state. The most dangerous municipality (São Paulo city) records an average of

[7] See the Department of Public Safety's website, linked here.

[8] About two-thirds of the observations are already geocoded. I am able to geocode 58% of the remaining observations based on the address of the offense.

[9] The true incidence of victimless crimes is notoriously difficult to measure accurately, and reporting rates differ across neighborhoods. These types of offenses, therefore, would probably be less reliable as outcome measures.

around 280,000 crimes a year, while the safest municipality records just one. Both panels look very similar, suggesting that population cannot account for differences in crime between municipalities.

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 their 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 A4 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 its 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 with iFood over 8 years.

Municipality and Neighborhood Characteristics Information on municipality and neighborhood characteristics come from various sources. Municipality boundary shapefiles and municipality population trends are from the Brazilian Institute for Geography and Statistics (IBGE). I use both to make maps of the distribution of crime across municipalities (Figure A3) and the expansion of iFood over time (Figure A4). 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:

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

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. The model is estimated using Poisson pseudo-maximum likelihood because the dependent variable is a count. Standard errors are clustered at the municipality level.[10]

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 municipalities that receive it later would be on the same crime trend absent the introduction of the delivery platform. Empirically, the lack of preexisting differences in crime between municipalities "treated" earlier and later provides support for this assumption. To further support the credibility of the parallel trends assumption, I estimate treatment effects using the method proposed in Callaway and Sant'Anna (2021), which accounts for the possibility that treatment effects are not constant across municipalities or over time. Also 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.[11]

3.2 Gig Work Reduces Crime

Table 1 presents the main results, estimates of Equation 1. Panel A uses the count of criminal offenses by municipality and year as the dependent variable. In column 1, which controls for municipality and year fixed effects, the coefficient of interest is negative and significant, implying that the introduction of the delivery platform reduces property crime by 10.4% on average—equivalent to 529 fewer crimes per year in each municipality. Columns 2 and 3 control for interactions of year fixed effects with (the log of) municipality GDP per capita and both the (the log of) municipality GDP per capita and (the log of) population, respectively. This accounts for potential differences in crime trends by market size, which could influence iFood's entry decision. The point estimates remain similar, suggesting these differences are not driving the results. Panel B repeats the same

[10]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 relaxing these restrictions.

[11]Personal interviews conducted with M. Biggi, ex-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 Levels

	(1)	(2)	(3)
	Panel A: Dependent Variable is **Crime (count)**		
Post iFood (=1)	-0.104***	-0.124***	-0.0946***
	(0.0189)	(0.0258)	(0.0306)
Dependent Variable Mean	5089	5089	5089
	Panel B: Dependent Variable is **Crime (per Capita)**		
Post iFood (=1)	-0.139***	-0.143***	-0.0944**
	(0.0410)	(0.0403)	(0.0430)
Dependent Variable Mean	1006	1006	1006
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	-	-
Year Fixed Effects X Pre-period log GDP/Capita		yes	yes
Year Fixed Effects X Pre-period log Population		-	yes
Observations	1,180	1,180	1,180

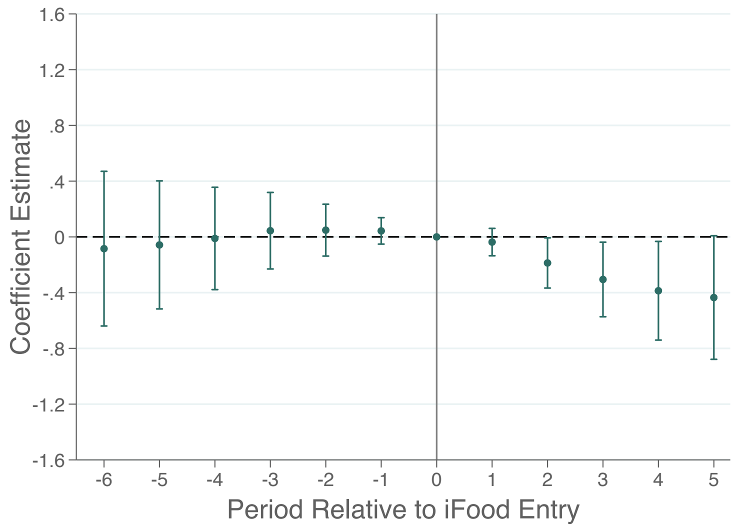
The unit of observation is a municipality-year. The sample is all municipalities with over 50,000 residents and all regressions are estimated using Poisson pseudo-maximum likelihood. The dependent variable is the number of criminal offenses in Panel A and the number of criminal offenses per 100,000 residents in Panel B. "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 and 3 control for municipality fixed effects and year fixed effects interacted with (the log of) pre-period GDP per capita and both the (the log of) pre-period population and GDP per capita, respectively. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

specifications using the number of criminal offenses per 100,000 residents as the dependent variable. The results closely match those in Panel A, with the baseline specification indicating a 13.9% decrease in crime per capita, suggesting the findings are not specific to populous municipalities with high total crime counts.

Next, I investigate the dynamic effects of the increase in delivery work on crime. Figure 1 plots the event study associated with Equation 1.[12] Consistent with the identification assumption, there are no preexisting differences in crime between municipalities that receive the delivery platform services earlier versus later: the coefficients for years prior to the introduction of iFood are indistinguishable from zero. The negative effect sets in one year after iFood is introduced and continues growing over time, reflecting the fact that new commercial establishments and consumers continue to join the app over time after it enters a municipality, as shown in Figure A5. To further explore dynamic effects, I present results using the method outlined by Callaway and Sant'Anna (2021) to address the possibility that estimates are biased because treatment effects are heterogeneous. Figure A7 plots estimates of the treatment effects disaggregated by year from this exercise and shows a very similar picture, indicating that heterogeneous treatment effects are not an important part of the story.

[12]The main event study restricts the sample to include periods with at least 20 municipalities in both treatment and control groups. Figure A6 displays the event study with the full sample.

Figure 1: Event Study: Effect on Crime (count)



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 is the number of criminal offenses. Standard errors are clustered by municipality and 95% confidence intervals are reported.

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, I separately estimate the effects for non-violent and violent crime (Table A2). 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 on individuals at the margin of committing non-violent offenses, resulting in a larger reduction in these crimes relative to violent ones. Moreover, I show evidence in section 4.2.1 of a large decline in violent crime in the lowest-income neighborhoods, where the overall effect is also concentrated.

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 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 for this sample. The point estimates are small and statistically indistinguishable from zero across columns, which suggests limited 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 property 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 significantly 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 desaggregates 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 when I look specifically at crime 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

This section explores the mechanisms behind the main results. First, I use differences in the returns to delivery work over the course of the day to explore whether an increase in the opportunity cost of crime is causing driving the main result. Second, I study how delivery work affects the spatial distribution of crime across neighborhoods and which locations drive the baseline result.

4.1 Differential Returns to Delivery Work

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).[13] 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

[13] 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 is 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:

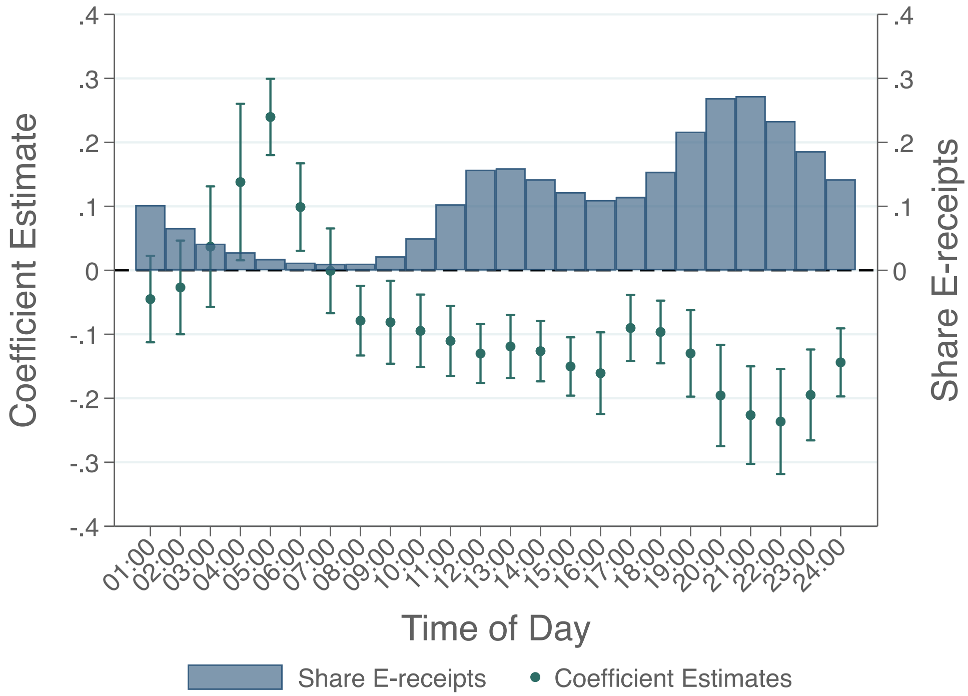
$$\text{Crime}_{hmt} = \exp\{\alpha_h + \delta_m + \phi_t + \sum_{r=1}^{24} \beta^r (\mathbb{1}_{mt}^{Post} \cdot \text{Time}_h^r) + \epsilon_{hmt}\} \tag{2}$$

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 regression specification controls for municipality, year, and time of day fixed effects, ensuring that the effect is estimated by comparing crime in a specific hour of the day and municipality, before and after the introduction of the delivery platform. 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 9:00a.m. onwards until it peaks during lunchtime, goes back down again 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. This suggests that effects are stronger when gains from work are higher. The fact that effects are strongest at times of day when delivery drivers are most likely to be engaged in delivery work is also a reassuring sign that the main estimates are truly capturing the effect of delivery since it is unclear *ex ante* why any other omitted trend would generate this precise pattern of crime reduction over the course of the day.

Table A5 tests more formally whether there are significant 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

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.

with delivery demand, and effects are negative and significant in all but the least busy quarter of the day. The fact that the magnitude of the effects is increasing with the returns to delivery work is suggestive evidence that the opportunity cost of crime is a relevant channel.

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 when demand is higher). 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 negative and significant in the two busiest quartiles of the day. In other words, offenders refrain from violent crime only when delivery work is most rewarding, consistent with opportunity cost as a driver of the negative effect. Overall, the results indicate 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 responds to differences in opportunity costs over the course of the day.

4.2 Effects on the Spatial Distribution of Crime

4.2.1 Effects by Neighborhood Income

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 disproportionally live and might have otherwise worked (e.g. Rengert, 2012).

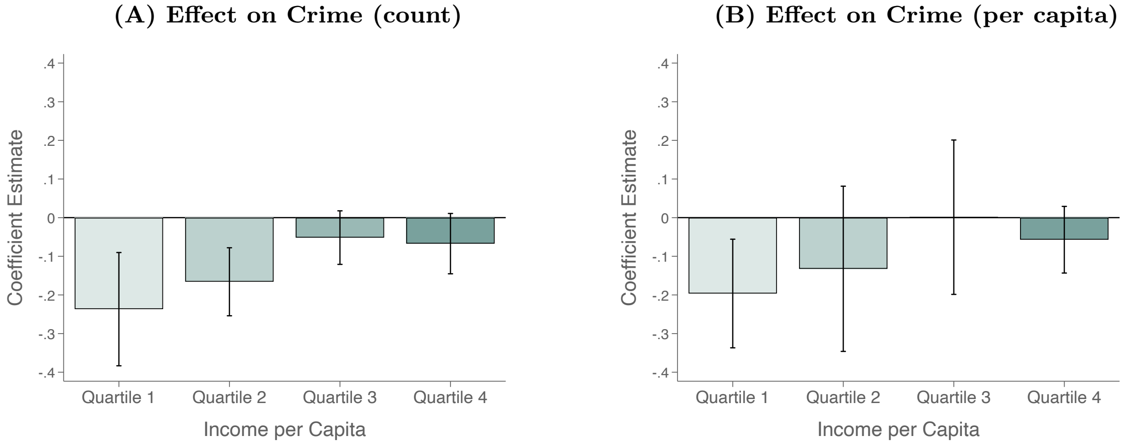
To examine effects by neighborhood, I divide São Paulo state into 0.04° by 0.04° grid cells. Each grid cell is roughly 20 square kilometers. The size of the grid cells was chosen such that the average number of grid cells per municipality approximates the average number of neighborhoods, subject to the aggregation of the gridded income and gridded population being feasible. For each grid cell, I calculate income per capita using gridded data on income and population. Figure A9 displays the map of São Paulo state divided into these grid cells and shaded according to income per capita. I then estimate a version of Equation 1 at the grid cell by year level:

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

where ℓ indexes grid cells, m indexes municipality, and t indexes year. I estimate Equation 3 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 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.

Figure A10 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, 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. This means that the average effect I find for violent crime in section 3.2, which is small compared to the effect on non-violent crime, is concealing a large effect on violent crime in the most dangerous neighborhoods. The larger negative effect on low-income, high-crime neighborhoods also suggests that the introduction of delivery work reduces inequality in exposure to crime across neighborhoods.

4.2.2 Effects by Local Delivery Demand

A second possible effect on the spatial distribution of crime is that the introduction of the delivery platform shifts offenses towards areas where delivery drivers work. This effect is likely to be stronger in more segregated cities, where mobile delivery jobs represent a significant change in the employment locations of low-skilled workers. I explore this possibility by estimating the effect of the introduction of iFood in or near streets that received iFood deliveries during the study period. To do this, I divide São Paulo state into $0.008° \times 0.008°$ grid cells (roughly 1 km^2 each) and use the geocoded delivery drop-off location from e-receipt data to identify which cells have received deliveries. I estimate the effect separately for these serviced cells, which make up roughly 15% of all grid cells. In addition, I examine whether the effect in these grid cells is different in the most

Table 2: Effect on Crime in Places with Delivery Presence

	Dependent Variable is **Count of**					
	Crime		**Non-violent Crime**		**Violent Crime**	
	All Municipalities	Unequal Municipalities	All Municipalities	Unequal Municipalities	All Municipalities	Unequal Municipalities
	(1)	(2)	(3)	(4)	(5)	(6)
Post iFood (=1)	-0.112***	-0.145***	-0.194***	-0.172***	-0.0473	-0.126**
	(0.0214)	(0.0475)	(0.0310)	(0.0419)	(0.0305)	(0.0579)
Grid Cell by Municipality FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Dependent Variable Mean	143	47	64	27	82	22
Observations	27,610	11,290	27,350	11,190	26,890	10,810

The unit of observation is a grid cell by municipality and year. All regressions are estimated using Poisson pseudo-maximum likelihood and the sample is grid cells that received at least one iFood delivery during the sample period in municipalities with over 50,000 residents. The dependent variable is the number of criminal offenses in columns 1 and 2, the number of non-violent criminal offenses in columns 3 and 4, and the number of violent offenses in columns 5 and 6. Even-numbered columns restrict the sample to municipalities with above-median inequality, as measured by the Gini coefficient (Figure A8). "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.

unequal municipalities, as proxied by their income per capita Gini coefficient (Figure A8).

The results are presented in Table 2. In column 1, the dependent variable is the number of criminal offenses and the sample includes all municipalities. The point estimate suggests a reduction in crime of 11.2%, which is remarkably similar to the estimated effect in all neighborhoods (Table 1 column 1, 10.4%). Column 2 zooms into the effect on above-median inequality municipalities, and shows the coefficient is similar to column 1, and, if anything, larger in magnitude (p=0.52). Columns 3-6 repeat the specifications in columns 1 and 2 for non-violent offenses (3 and 4) and violent offenses (5 and 6), and show the exact same pattern: coefficient estimates are very similar to the main effects (Table A2), even in the most unequal municipalities. This suggests that a shift in the location of low-skilled workers due to an expansion in work opportunities does not lead to a relocation of crime to the new work site.

Together with the estimates in the previous section (4.2.1), these findings suggest that crime is not decreasing in some places and increasing in others, so that the main results do not mask a spatial displacement of crime. Instead, there appears to have been a reduction across all types of 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 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 for at least five years. This the first study to show that expanding flexible work opportunities can generate sustained reductions in crime in a developing-country, where crime urban rates are high 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, I find that 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, I find no evidence that crime is displaced toward high-income neighborhoods or areas with greater delivery demand, even in municipalities with higher income inequality where segregation is most pronounced.

Delivery work could have synergies with crime—by increasing free time, mobility, or opportunities for cover—that would push the effect in the opposite direction. However, I instead find a sizable and persistent reduction in crime. These findings may extend to other forms of flexible work, which are on the rise around the world and were accelerated by the COVID-19 pandemic. More broadly, the heterogeneous effects I document indicate that connecting low-skilled workers to job opportunities in wealthier areas may be a powerful and scalable way to reduce crime and narrow gaps in safety across neighborhoods, without shifting crime elsewhere.

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.

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.

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

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.

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.

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

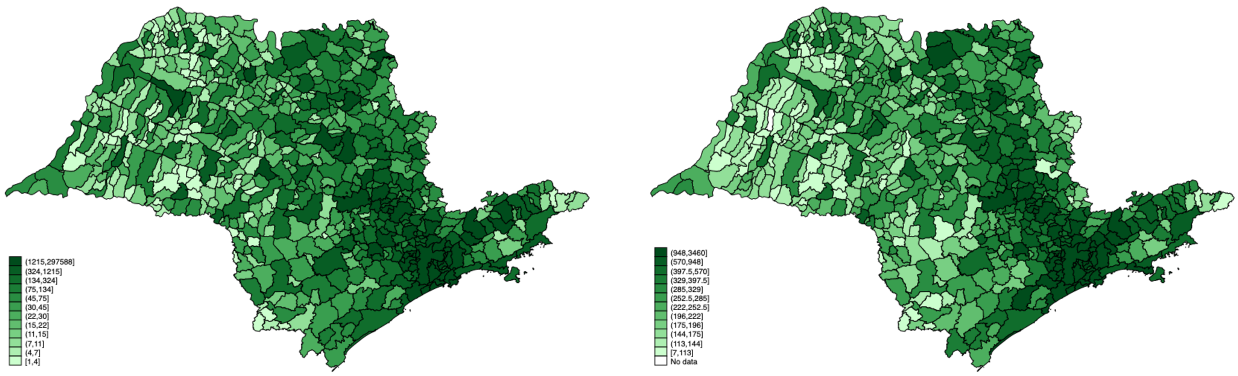
27/04/2022 | Delivery drivers, Releases

Position on crimes committed by people using iFood bags

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

Figure A3: Crime Across Municipalities in São Paulo

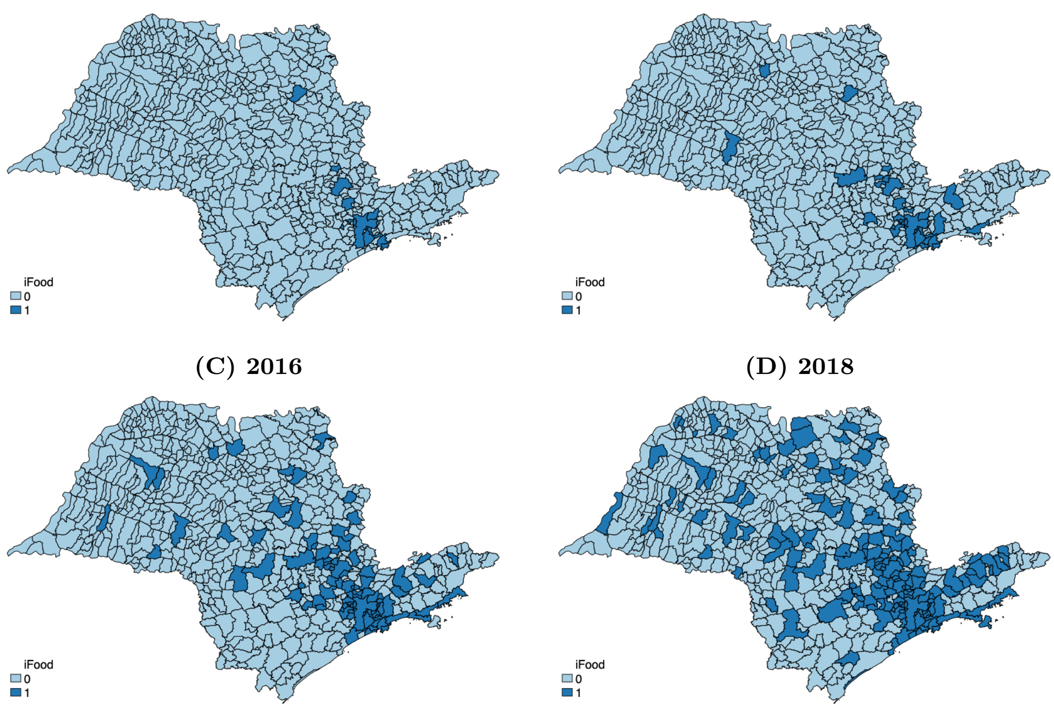
(A) Count per year **(B) Count per year per 100,000 people**



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.

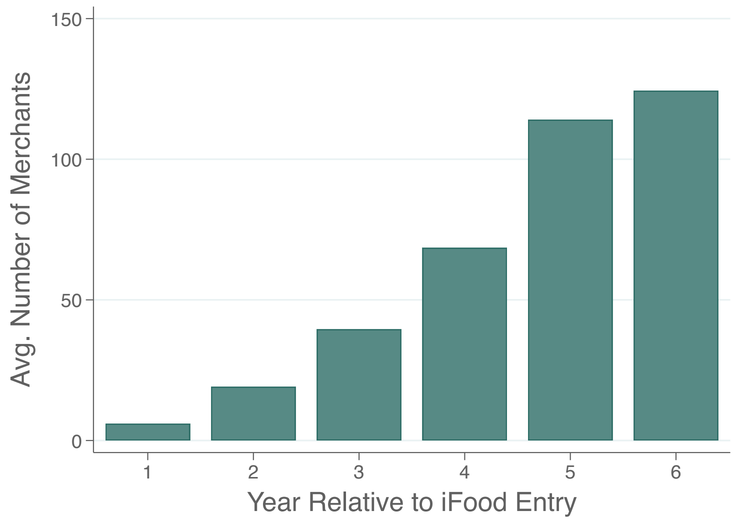
Figure A4: Rollout of iFood Over Time

(A) 2012 **(B) 2014**



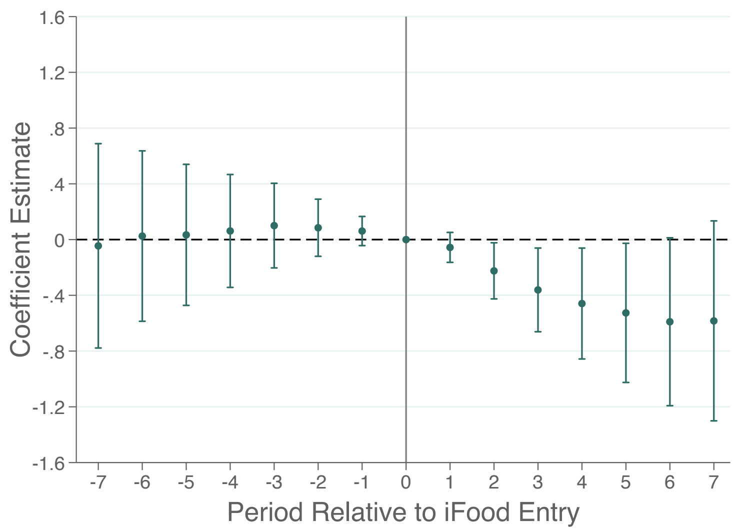
This figure shows the municipalities that have iFood services in 2012 (Panel A), 2014 (Panel B), 2016 (Panel C), and 2018 (Panel D).

Figure A5: Number of Merchants Registered with iFood Over Time



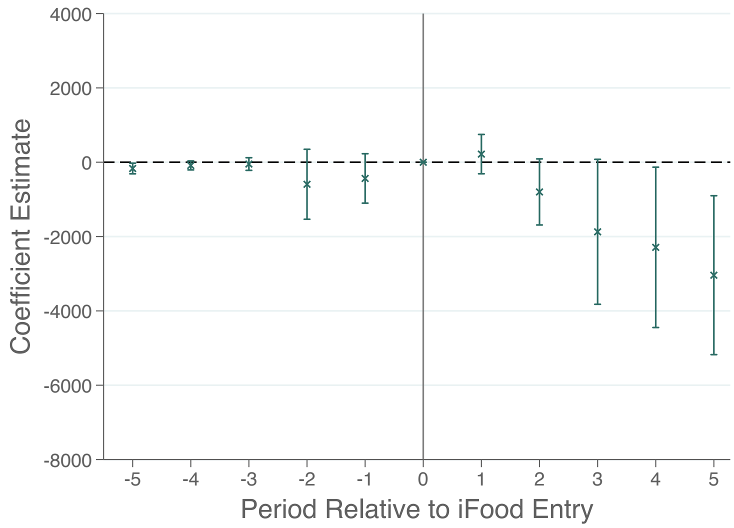
This figure displays the average number of merchants (commercial establishments) per 100,000 residents registered with iFood in each municipality over time.

Figure A6: Event Study with no Trimming



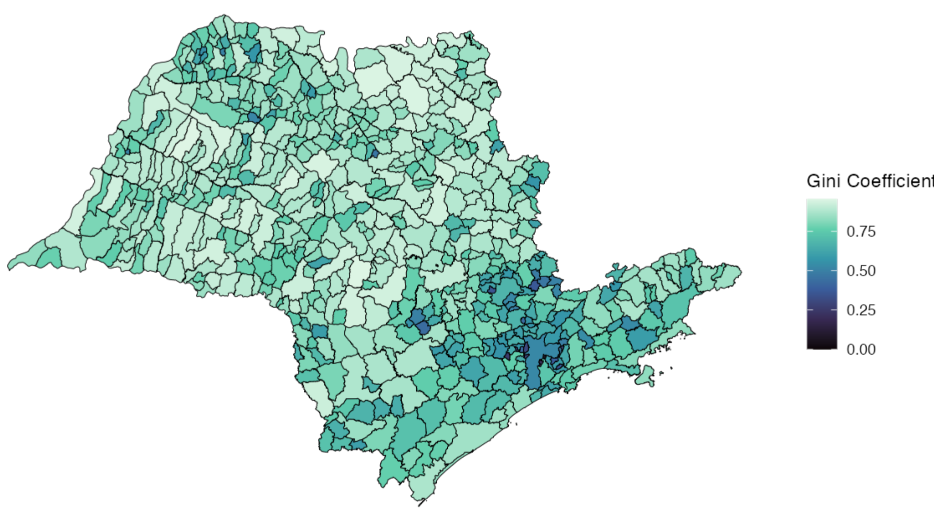
This figure shows dynamic treatment effects over time. The regression is estimated using Poisson pseudo-maximum likelihood and the sample is all municipalities with over 50,000 residents. The unit of observation is a municipality-year. The dependent variable is the number of criminal offenses. Standard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

Figure A7: Event Study Accounting for Staggered Rollout



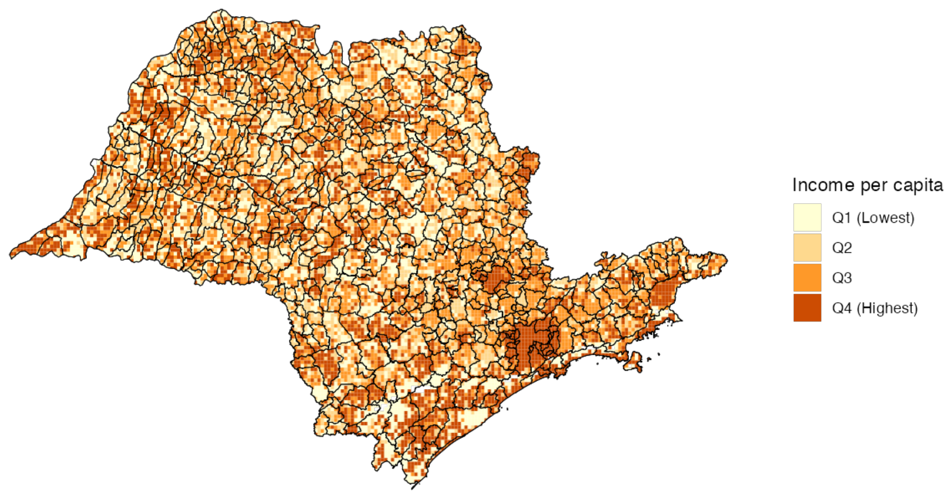
This figure shows treatment effects over time estimated using the method outlined in Callaway and Sant'Anna (2021). The sample is all ever-treated municipalities with over 50,000 residents, and is restricted to periods in which at least 20 municipalities are observed in both the treatment and control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

Figure A8: São Paulo State Shaded by Gini Coefficient



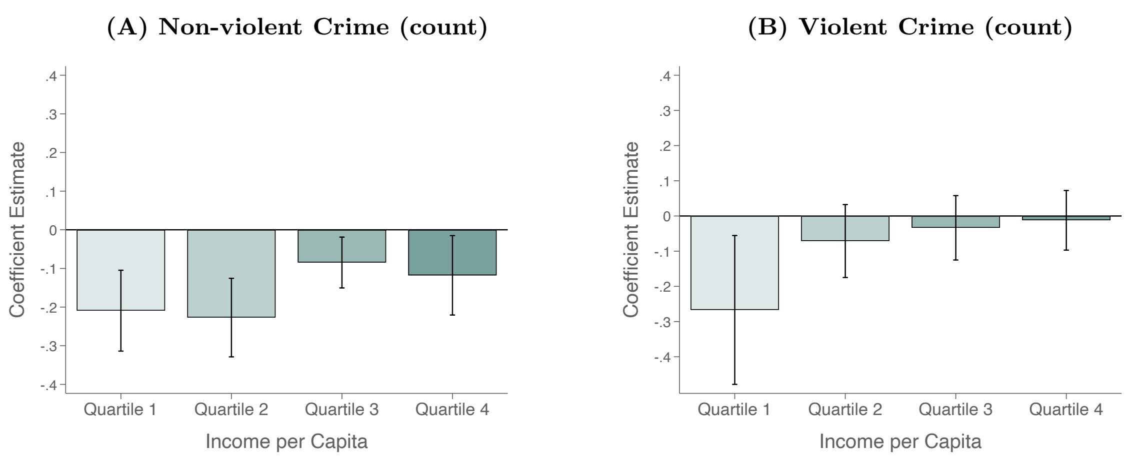
This figure shows a map of São Paulo state with municipalities shaded by their Gini coefficient, calculated from the income distribution of $0.04^\circ \times 0.04^\circ$ grid cells within each municipality. Lighter shades indicate higher Gini coefficients and greater income inequality.

Figure A9: São Paulo State Shaded by Income per Capita



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

Figure A10: 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.

Table A1: Effect on Crime (count): Relaxing Population Restriction

	Dependent Variable is **Crime (count)**		
	(1)	(2)	(3)
Post iFood (=1)	-0.233***	-0.226***	-0.246***
	(0.0241)	(0.0237)	(0.0327)
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	-	-
Year Fixed Effects X Pre-period log GDP/Capita		yes	yes
Year Fixed Effects X Pre-period log Population		-	yes
Dependent Variable Mean	969	969	969
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. "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 and 3 control for municipality fixed effects and year fixed effects interacted with (the log of) pre-period GDP per capita and both the (the log of) pre-period population and GDP per capita, respectively. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A2: Effects Disaggregated by Type of Offense

	Dependent Variable is **Count of**	
	Non-violent crime	**Violent crime**
	(1)	(2)
Post iFood (=1)	-0.172***	-0.0452*
	(0.0333)	(0.0238)
Municipality Fixed Effects	yes	yes
Year Fixed Effects	yes	yes
Dependent Variable Mean	2209	2880
Observations	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. The dependent variable is the number of non-violent criminal offenses in column 1 and violent offenses in column 2. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after. Both 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 A3: Spillover Effects on Crime in Neighboring Municipalities

	(1)	(2)	(3)
	Panel A: Dependent Variable is **Crime (count)**		
Neighbor's Post iFood (=1)	0.0310	0.0245	0.0253
	(0.0727)	(0.0719)	(0.0727)
Dependent Variable Mean	21	21	21
	Panel B: Dependent Variable is **Crime (per Capita)**		
Neighbor's Post iFood (=1)	-0.0134	-0.0153	-0.0127
	(0.0627)	(0.0622)	(0.0609)
Dependent Variable Mean	178	178	178
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	-	-
Year Fixed Effects X Pre-period log GDP/Capita		yes	yes
Year Fixed Effects X Pre-period log Population		-	yes
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 Panel A and the number of criminal offenses per 100,000 residents in Panel B. "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. Column 1 controls for municipality and year fixed effects. Columns 2 and 3 control for municipality fixed effects and year fixed effects interacted with (the log of) pre-period GDP per capita and both the (the log of) pre-period population and GDP per capita, respectively. 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 outdoors, and in column 2, it is the number committed indoors. Columns 3 and 4 focus specifically on offenses involving the theft of a personal item, with column 3 showing those committed outdoors and column 4 those committed indoors. "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
Time of Day Fixed Effects	yes	yes	yes
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
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
Time of Day Fixed Effects	yes	yes	yes
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
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. It is also interacted with binary variables that equal one if the time of day belongs to that quartile of crime. 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.