The Gig Economy and Crime in Brazil*

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Abstract

This study leverages the staggered rollout of the largest food delivery platform in Brazil (iFood) across municipalities in São Paulo state to investigate how the expansion of gig work affects the level and geographic distribution of crime. This relationship is not clear ex ante: while a positive labor market shock should increase the opportunity cost of crime, greater work flexibility also makes it easier to shift back and forth between criminal activity and employment. Moreover, by employing low-skilled workers to deliver goods in high-income neighborhoods, gig work could alter the spatial incidence of crime, especially in very segregated cities. I find that the introduction of iFood reduced crime, including violent crime, and that this effect persisted over time. The effect is larger in magnitude at times of day when the returns to delivery work are highest, but is still present when delivery demand is low. I find no evidence that delivery work is shifting crime towards neighborhoods that demand delivery services, and the effect is stronger in lower-income neighborhoods, where delivery workers tend to reside.

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1 Introduction

The digital revolution of the twenty-first century has led to new, nontraditional work arrangements, commonly referred to as "gig" employment. 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, transportation and delivery apps currently employ roughly 1.5 million people as drivers, a number that has grown 984% in the last 5 years. 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.[1]

This study investigates the effect of this change in the nature of employment on crime by focusing on the expansion of delivery platform jobs. The growth of delivery jobs was a positive labor market shock to young, unskilled men, which is the population most likely to commit "blue collar" crime. It is unclear ex-ante whether the expansion of delivery work increases or decreases crime. 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). On the other hand, the flexibility of gig work means employment can be easily combined with criminal activity. The increase in flexible jobs can also increase free time, which can in turn increase crime (Jacob and Lefgren, 2003; Dahl and DellaVigna, 2009). Moreover, delivery can also shift the location of employment: low-skilled workers who would otherwise likely work in lower-income neighborhoods are hired to deliver goods to wealthier parts of the city. This could relocate crime to these places, especially in geographically segregated cities where potential offenders do not regularly visit rich neighborhoods. In fact, it is common to see anecdotes in the news about individuals using delivery uniforms as cover for committing crime (Figure A1).[2] It is therefore necessary to turn to data in order to understand how the introduction of flexible and mobile employment affects crime.

I exploit the introduction of the largest food delivery platform in Brazil, iFood, into municipalities in São Paulo state to investigate how the expansion of digital platform employment affects crime.[3] The state of São Paulo has reliable geocoded and time-stamped crime data, which also allows me to explore the channels behind the effect. The empirical strategy combines 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. The main result is that the introduction of the delivery platform into a municipality reduces the number of criminal offenses by 11.2%. This is equivalent to 501 fewer offenses per municipality and year on average. This negative effect extends to violent

[1] According to a 2022 report by the Brazilian Institute for Applied Economics Research (IPEA), reported by TecnoBlog in the article linked here.

[2] 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, which is also linked here

[3] São Paulo is home to 44 million people, about one fifth of the Brazilian population, and a quarter of all municipalities served by iFood in Brazil.

property crime, when there is use of force or a weapon, and persists up to four years after the delivery platform is introduced.

Next, I examine the forces behind the negative effect of the increase in delivery work on crime. The first test is designed to investigate whether the increase in the opportunity cost of crime as a result of the expansion of delivery jobs is driving the negative effect I observe. Food deliveries are concentrated around mealtimes, meaning that the returns to employment (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 opportunity cost is a relevant channel, effects should be stronger when returns to employment are higher. I find that effects are significantly stronger when delivery demand is highest, and that this is particularly true for violent crime, but effects are also present when delivery demand is very low, suggesting evidence consistent with effects of total income on criminal participation.

The second and third tests explore the spatial incidence of the effect. The increase in delivery jobs could change the geography crime for two reasons. First, separate work in criminology has documented that individuals do not tend to travel long distances to commit crime, which implies the effect might be stronger in lower-income neighborhoods, where delivery drivers disproportionately work and live (e.g. Rengert, 2012). To investigate this, I estimate effects separately for high and low income neighborhoods using gridded data on income per capita and find that the effect is strongest in the lowest-income neighborhoods. Below-median income neighborhoods register three times more crime than above-median income neighborhoods at baseline, which means that the shock is dampening the inequality in safety across different parts of the city. Second, delivery work shifts the location of employment towards places that demand delivery services, which could increase crime in these places. To check for this, I estimate the effect separately for local areas (1 km^2 grid cells) that did or did not receive deliveries during the study period. I find no evidence that delivery work is shifting crime towards places that demand iFood services: the effects in these places is also negative and statistically indistinguishable from the effect in places that do not receive deliveries.

Related Literature This project contributes to past work examining the costs and benefits of the introduction of gig work.[4] For example, using data on hourly earnings and driving, Chen et al. (2019) show that drivers 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 differences in preferences and constraints across genders. To my knowledge, this is the first paper to investigate the effect of gig work on crime, which is

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

important given how widespread this type of employment has become and how many of these jobs affect individuals at risk of offending.

My results also add to the existing evidence on the relationship between labor market conditions and crime. Britto et al. (2022), Khanna et al. (2021), Dell et al. (2019), and Dix-Carneiro et al. (2018) show that financially-motivated crime increases following mass layoffs in different Latin American countries. Relatedly, Machin and Meghir (2004) find that relative decreases in wages of low-skilled workers in the United Kingdom lead to increases in crime during the 1970s and Gould et al. (2002) show a causal link between the labor market prospects of young, unskilled men, and crime rates in the 1980s and 1990s in the United States.[5] This paper builds on this evidence by examining the effect of a large shock to *flexible* employment, which has become increasingly common in the last decade and could be very different from the effect of shocks to traditional, full-time jobs. A small related literature investigates the determinants of the spatial distribution of crime inside cities, such as density and connectedness (Glaeser et al., 1996; Khanna et al., 2022; Lafrogne-Joussier and Rollet, 2023). This study also adds to this work by documenting how shifting the location of low-skilled employment affects the geographic distribution of crime.

The paper is organized as follows. Section 2 provides more information on the delivery platform rollout and describes the data. Section 3 introduces the empirical strategy and reports the results, 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 food delivery platform market in Brazil.[6] 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.[7] 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

[5]Other work shows that crime is financially motivated by investigating the relationship between benefit payments and crime and finds that crime is lower when individuals are eligible for unemployment benefits (Khanna et al., 2023) and that the temporal pattern of property crime follows the (inverse) pattern of benefit disbursements when payments are concentrated (Foley, 2011; Watson et al., 2020).

[6]According to estimates by Statista, a global data and business intelligence platform. See the link here.

[7]As reported by CADE's website, linked here.

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.[8]

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).

2.2 Data

Crime Data on crime come from São Paulo State's Department of Public Safety.[9] 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 because data are not available for other types of crime going back to 2010. Using the universe of criminal incident reports for all types of crime available for January 2022, I check that, reassuringly, property crimes make up 98% of all kinds of criminal incident reports. The sample stops in 2019 to exclude years that were affected by the Covid-19 pandemic, when consumer behavior and criminal activity were atypical.[10]

These data capture a comprehensive picture of property crime because victims have strong incentives to report crime and reporting costs are low. Insurance companies require incident reports in order to issue reimbursements and employers ask for reports to justify employee absenteeism. Submitting an incident report online is also an option during the study period, so the costs of filing

[8] The results of this survey appear in the paper by Callil and Picanço (2023), cited above.

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

[10] About two-thirds of the observations are already geocoded. I am able to geocode 58% of the non-geocoded observations based on neighborhood address. The remaining observations cannot be geocoded because the address information is missing, therefore I match them at the municipality level.

a report are very low. In addition, 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 3.3.2 and 3.3.3). The main downside of data from incident reports is that they miss victimless crimes, such as drug offenses or prostitution.[11]

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 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 information from iFood on the first year they observe an order in a municipality to code the timing of entry. 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 characteristics and neighborhood characteristics come from a set of different sources. Municipality boundary shape-files and municipality population over time are obtained 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 ef-

[11] 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 unhelpful as outcome measures.

fects differ across neighborhoods with different socio-economic status, I use gridded data on income from Kummu et al. (2018) and gridded data on population from Landsat to construct a measure of pre-period income per capita at the neighborhood level.

3 Results

3.1 Empirical Strategy

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

The coefficient of interest is β, which captures the causal 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 flexible employment 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. It is also reassuring that delivery platforms do not select to enter cities based on crime rates and are only concerned with the size of the potential market for their services.[12] I also estimate effects separately for each year using the method proposed in Callaway and Sant'Anna (2021) to account for the possibility that treatment effects are not constant across municipalities or over time.

[12] Personal interview conducted with M. Biggi, ex-manager at UberEats (one of iFood's main competitors during the study period), May 31st, 2023.

Table 1: Effect on Crime Levels

	Dependent Variable is **Crime (count)**		
	(1)	(2)	(3)
Post iFood (=1)	-0.112***	-0.113***	-0.081***
	(0.019)	(0.020)	(0.030)
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	-	-
Year Fixed Effects X Pre-period log GDP/Capita		yes	-
Year Fixed Effects X Pre-period log Population		-	yes
Dependent Variable Mean	4478	4478	4478
Observations	1,350	1,350	1,350

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 and 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 (the log of) pre-period population, respectively. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

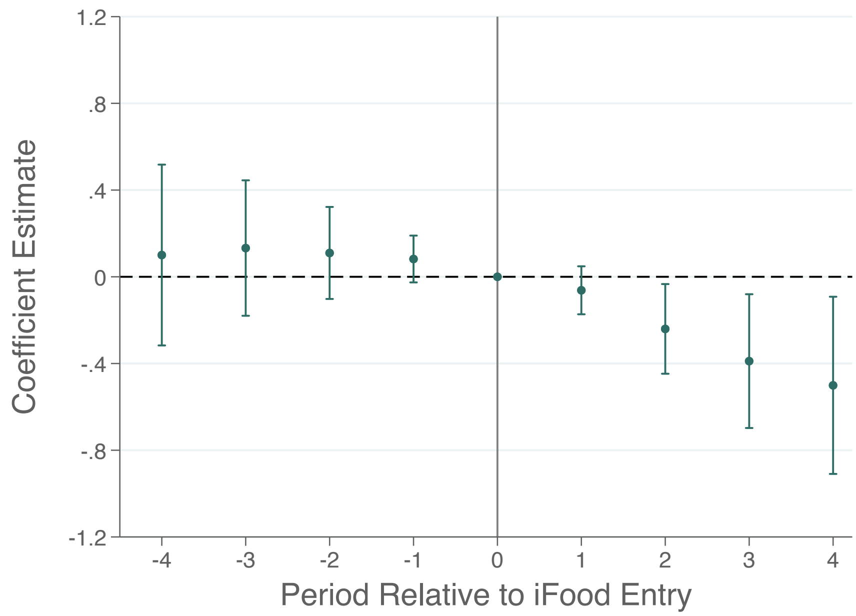
3.2 Gig Work Reduces Crime

3.2.1 Baseline Results

Table 1 documents the main results, estimates of Equation 1. The dependent variable is the count of criminal offenses by municipality and year in all columns. The first column controls for municipality and year fixed effects, and the coefficient of interest is negative and significant, meaning the introduction of the delivery platform reduces property crime. The point estimate implies that the increase in delivery work in municipalities that receive iFood services reduces crime by 11.2% on average. This is equivalent to 501 fewer crimes per year in each municipality. The second and third columns replicate this result, controlling for year fixed effects interacted with (the log of) municipality GDP per capita and (the log of) population, respectively. This controls for potential differences in crime trends between municipalities with larger and smaller market size, which is taken into consideration in iFood's choice of entry. The point estimate is similar, suggesting that any differences in crime trends between poorer and richer municipalities and between more and less populous municipalities are not driving the results.

Next, I investigate the dynamic effects of the increase in delivery work on crime. Figure 1 plots the event study associated with Equation 1. 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 idea that new commercial establishments and consumers continue to join the

Figure 1: Event Study: Effect on Crime Levels



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.

app over time after it enters a municipality.

This average negative effect could mask differences in the effect on 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. I find that the effect is larger in magnitude for non-violent crime, which reduces by 18%, than for violent crime, which reduces by 5.2%. This pattern is consistent with the idea that the shock is more relevant for people on the margin between committing a non-violent offense or not, leading to a larger reduction in those types of offenses compared to violent crimes. With that being said, in section 3.3.2 I show evidence of a large and significant decrease in violent crime in poorer neighborhoods.

3.2.2 Extensions

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 A2 replicates the structure of Table 1 for this sample. The point estimates are negative but small and statistically indistinguishable from zero across columns, suggesting that any spillover effects are limited. This is consistent with the fact that municipalities are relatively large administrative units, meaning cross-border commuting for work or criminal activity is probably 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, this could reduce crime by lowering opportunities for victimization. To investigate this, Table A3 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 main result.

3.3 Mechanisms

3.3.1 Effects by Differential Returns to Delivery Work

Traditional 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 this opportunity cost channel because large shocks to the labor market usually affect other factors that determine crime (Rose, 2018). 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). This makes it impossible to isolate the effect of changes in the opportunity cost of crime from the effect of these other variables.

The fact that drivers are free to choose when to work and the returns to delivery work vary predictably across hours of the day allows me to check whether the opportunity cost of crime is driving the main effect. Delivery work 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 employment 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 employment 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 the total income from employment being sufficient to stop drivers from offending at all times.

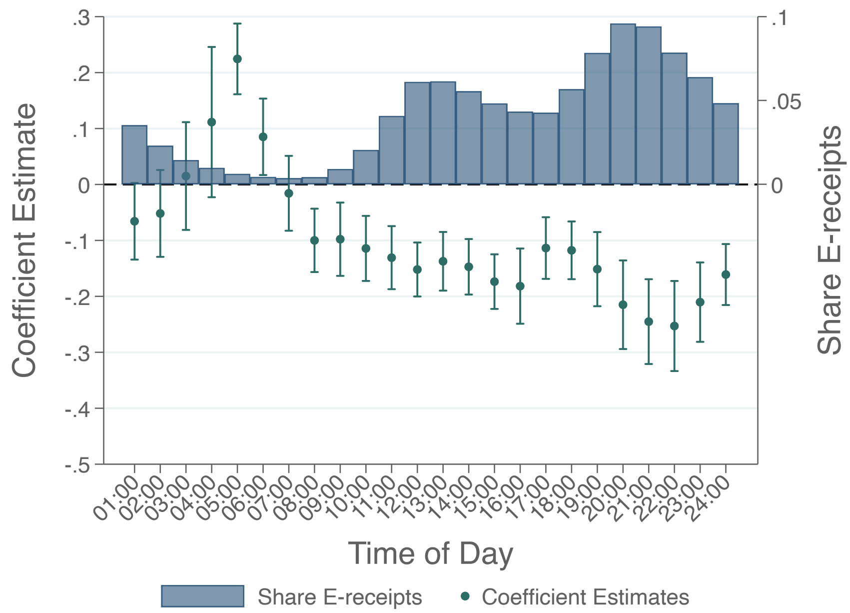
Using the time of day when each offense was committed, I separately estimate the effect of the introduction of the delivery platform for each hour of the day to test whether increases in the opportunity cost of crime are driving the main result. The unit of observation is a time of day by municipality 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 results of this regression with 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 the early morning hours of the day, 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 potential gains from employment 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 introduction of delivery jobs does in fact affect potential offenders.

Table A4 tests whether the differences in the magnitude of the effect follow differences in the returns to delivery work. 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 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 employment is suggestive evidence that the opportunity cost of crime is a relevant channel.

Columns 2 and 3 estimate this specification separately for non-violent and violent crime, respectively. When the dependent variable is non-violent crime, the effects are very similar across quartiles of delivery demand. On the other hand, when the dependent variable is violent crime the effect is only negative and significant for the two busiest quartiles, when returns to employment are

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.

at their highest. In other words, offenders only refrain from violent crime when employment is most rewarding, which is evidence that the opportunity cost of crime is an important driver of the effect on violent crime. To rule out the possibility that factors other than delivery demand are generating these patterns, 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 A5 shows the results, which are qualitatively similar to Table A4. This further supports the interpretation that violent crime is responding to changes in the opportunity cost of crime that result from the increase in delivery jobs.

These results suggest that models assuming a mutually exclusive choice between criminal activity and employment—based on the relative returns to each—are better suited to explain participation in violent crime than in non-violent crime. One possible reason is that these models presume both employment and criminal activity are viable options, which may be an unrealistic assumption for low-skilled workers in developing countries. An alternative interpretation consistent with the findings is that individuals engage in non-violent crime only when employment opportunities are unavailable, and that the introduction of the delivery platform is expanding access to these opportunities.

3.3.2 Effects on the Spatial Distribution of Crime: 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 17 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. For each grid cell, I calculate income per capita using gridded data on income and population. Figure A6 displays the map of São Paulo state divided into these grid cells and shaded according to income per capita.

To explore differential effects by neighborhood income I estimate an extended version of the main regression equation:

$$\text{Crime}_{\ell mt} = \exp\{\alpha_{\ell m} + \delta_t + \rho \cdot \mathbb{1}_{mt}^{Post} \cdot \text{Low Income}_{\ell} + \phi \cdot \mathbb{1}_{mt}^{Post} \cdot \text{High Income}_{\ell} + \epsilon_{\ell mt}\}. \qquad (2)$$

The unit of observation is a grid cell ℓ in municipality m and year t. $\alpha_{\ell m}$ and δ_t are grid cell by municipality and year fixed effects. $\text{Crime}_{\ell mt}$ is the number of crimes in a grid cell by municipality and year. $\mathbb{1}_{mt}^{Post}$ is a binary variable that equals one after iFood has been introduced in each municipality, as above. $\text{High Income}_{\ell}$ (Low Income_{ℓ}) is an indicator that equals one if the grid cell has above (below) median income. As before, the model is estimated using Poisson pseudo-maximum likelihood and standard errors are clustered at the municipality level. The coefficients of interest are ρ and ϕ, which capture the causal effect of the introduction of the delivery platform on crime in low and high income neighborhoods, respectively. If the increase in gig work primarily affects individuals who would offend in low-income neighborhoods, we would expect $\rho < 0$ and $\rho \neq \phi$.

Table 2 displays the results. In the first two columns the dependent variable is the number of crimes in a grid cell by municipality and year. In column 1, "high" and "low" income grid cells are split according to the median value of the income per capita distribution. The effect is negative and significant for both above- and below-median income grid cells, but is 7 percentage points larger in magnitude for below-median income grid cells. This is the pattern we would expect if individuals affected by the employment shock are otherwise more likely to commit crime in lower-income neighborhoods.

To zoom into the effect in the poorest areas, column 2 splits grid cells according to the 25th

Table 2: Effects by Neighborhood Income

	High/Low Split Percentile			
	50	25	25	25
	Dependent Variable is **Count of**			
	Crime		**Non-violent Crime**	**Violent Crime**
	(1)	(2)	(3)	(4)
High Income X Post iFood (=1)	-0.077***	-0.099***	-0.166***	-0.037*
	(0.028)	(0.018)	(0.027)	(0.022)
Low Income X Post iFood (=1)	-0.146***	-0.190***	-0.247***	-0.167***
	(0.027)	(0.051)	(0.069)	(0.062)
p-value, High = Low	0.087	0.073	0.171	0.033
Grid Cell by Municipality Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Dependent Variable Mean	95	95	49	83
Observations	63,120	63,120	52,210	41,010

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 grid cell by municipality and year. The dependent variable is the number of criminal offenses in columns 1 and 2, the number of non-violent offenses in column 3, and the number of violent offenses in column 4. "Post iFood" is a binary variable that equals zero before iFood is introduced and one after."High Income" ("Low Income") is an indicator that equals one if the grid cell is above (below) the percentile split, indicated at the top of the column. 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.

percentile of the income per capita distribution, so that "low income" now includes the poorest 25% of neighborhoods. The effect in the poorest neighborhoods is approximately twice the magnitude of the effect on the richest 75% (p=0.07). In other words, the shock reduces crime everywhere, but the effect is significantly stronger in the poorest parts of the city. The poorest quartile of neighborhoods records roughly three times more crime than the richest quartile, which means the introduction of the delivery platform alleviates the geographic inequality in safety across neighborhoods.

Columns 3 and 4 check whether the difference in effects across neighborhoods holds for non-violent and violent crime separately. There is no significant difference in the effect on non-violent crime between the poorest quartile of grid cells and the rest, the effect on violent crime is almost entirely driven by decreases in crime in the poorest grid cells. These neighborhoods experience a 16.7% 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. These differences across neighborhoods mean that the incidence of the effects of an employment shock targeted to low-skilled workers is geographically uneven and help to dampen differences in crime rates across different parts of the city.

3.3.3 Effects on the Spatial Distribution of Crime: Delivery Demand

A second hypothesis is that the introduction of the delivery platform is changing the geographic distribution of crime by shifting offenses towards areas where delivery drivers work. I explore this possibility using two strategies. The first test separates the effect into neighborhoods with above and below median delivery demand per capita using a similar specification to the one described in section 3.3.2. The second compares the effect of the introduction of iFood in or near streets that received iFood deliveries during the study period with those that did not. To do this, I divide São Paulo state into 0.008° by 0.008° grid cells, each measuring roughly 1 square kilometer. I check whether there was a delivery in each grid cell using the geocoded delivery drop-off location from the e-receipt data. I use this information to estimate a similar specification to the one described in section 3.3.2:

$$\text{Crime}_{\ell mt} = \exp\{\alpha_{\ell m} + \delta_t + \rho \cdot \mathbb{1}_{mt}^{Post} \cdot \text{Delivery}_\ell + \phi \cdot \mathbb{1}_{mt}^{Post} \cdot \text{No Delivery}_\ell + \epsilon_{\ell mt}\}. \tag{3}$$

Again, the unit of observation is a grid cell ℓ in municipality m and year t. $\alpha_{\ell m}$ and δ_t are grid cell by municipality and year fixed effects. $\text{Crime}_{\ell mt}$ is the count of offenses in a grid cell by municipality and year. $\mathbb{1}_{mt}^{Post}$ is a binary variable that equals one after iFood has been introduced in each municipality, as above. "Delivery" is a binary variable that equals one if there was any delivery made to grid cell ℓ and zero otherwise, and "No Delivery" is its opposite. As before, the model is estimated using Poisson pseudo-maximum likelihood and standard errors are clustered at the municipality level. The coefficients of interest are ρ and ϕ, which capture the causal effect of the increase in delivery work on crime in grid cells that demand the service and grid cells that do not, respectively. If shifting the location of work to grid cells that demand iFood services shifts crime towards these places, we would expect $\rho > 0$ and $\rho \neq \phi$.

The results are presented in Table 3. Column 1 shows the effect of the introduction of iFood in neighborhoods with above- and below-median delivery demand. There is no evidence that crime is shifting toward grid cells with higher demand for iFood services: the point estimates are negative and statistically significant for both high- and low-demand areas, indicating that crime is also declining in these locations. Column 2 separates the effect on streets that did and did not receive an iFood delivery during the sample period. Again, both coefficients are negative and statistically significant, suggesting that crime is not increasing in areas where deliveries occur. If anything, the magnitude of the effect is larger for streets that received an iFood delivery than for those that did not. This suggests that, when accompanied by expanded employment opportunities, a shift in the location of low-skilled workers does not lead to a relocation of crime to the new employment site.

4 Conclusion

This paper leverages the staggered rollout of the largest food delivery platform in Brazil to study the effect of gig work on crime. I find that the introduction of the delivery platform reduced property crime by 11.2% on average. This effect extends to more violent crime, when there is use of force or a weapon, and persists four years after the introduction of the delivery platform. Turning to the

Table 3: Effect on Crime by Delivery Presence

	Dependent Variable is **Crime (count)**	
	(1)	(2)
High Delivery Demand X Post iFood (=1)	-0.124***	
	(0.022)	
Low Delivery Demand X Post iFood (=1)	-0.082***	
	(0.039)	
iFood Delivery X Post iFood (=1)		-0.136***
		(0.025)
No iFood Delivery X Post iFood (=1)		-0.059**
		(0.025)
p-value for difference	0.3573	0.0164
Grid Cell by Municipality Fixed Effects	yes	yes
Year Fixed Effects	yes	yes
Dependent Variable Mean	152	31
Observations	38,810	195,300

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 grid cell by municipality and year. 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. "High Delivery Demand" ("Low Delivery Demand") is an indicator that equals one if the grid cell has above (below) median orders per capita. "iFood Delivery" and "No iFood Delivery" are indicators that equal one if the grid cell did or did not receive at least one iFood delivery, respectively. 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.

mechanisms driving the results, I find some evidence that the reduction in violent crime is stronger at times of day when the returns to delivery work are highest. This means the opportunity cost of crime is a channel driving the results for these types of offenses, above and beyond the increase in income from employment. Finally, I document that the spatial incidence of the effect is not even because effects are larger in lower-income neighborhoods, where delivery drivers tend to live. With that being said, I find no difference in the effect between local areas that receive deliveries and those that do not, indicating that crime is *not* shifting towards places where drivers deliver as a result of the change in employment location.

Due to the fact that delivery work has synergies with crime that would push the effect to be positive, it is likely that the negative effect I find for the introduction of iFood extends to the expansion of other flexible jobs. Moreover, the differential effects by neighborhood suggest that increasing earnings for low-skilled workers by giving them opportunities in high income neighborhoods can be a powerful way to curb crime and reduce the differences in safety across neighborhoods, *without* shifting crime towards the wealthier parts of the city.

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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.

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

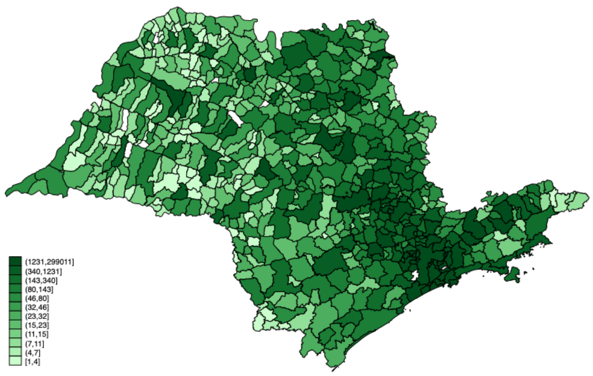
Comunicado

ifood news

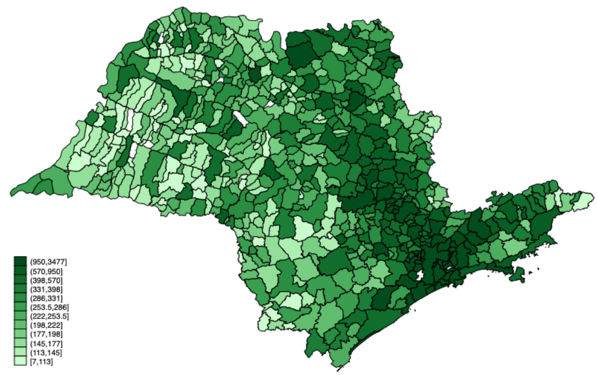
This figure shows a screenshot of a blog post published by iFood in 2022 describing the steps they take to mitigate crime committed by delivery drivers. The blog post can be found under this link.

Figure A3: Crime Across Municipalities in São Paulo

(A) Count per year



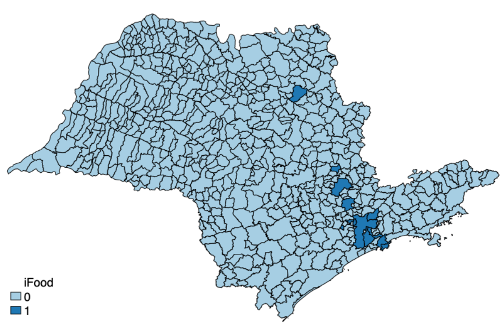
(B) Count per year per 100,000 people



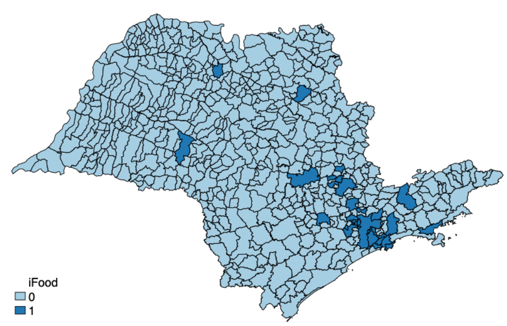
This figure shows the distribution of crime across municipalities in the state of São Paulo. In Panel A, municipalities are shaded according to the average count of criminal offenses registered by precincts per year from 2010 to 2019. In Panel B, municipalities are shaded according to the average count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

Figure A4: Rollout of iFood Over Time

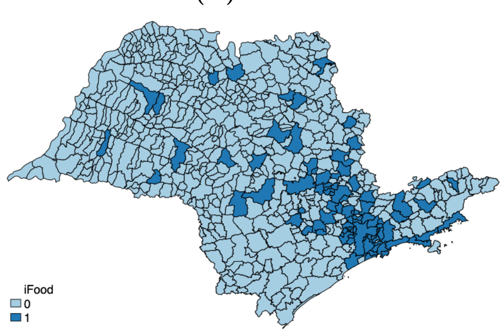
(A) 2012



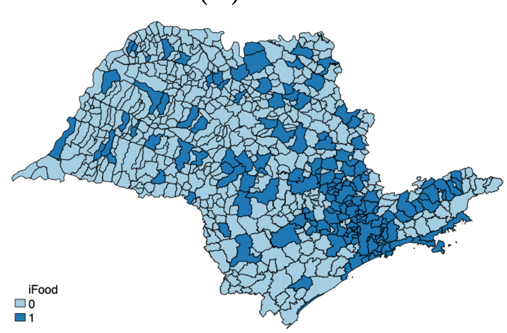
(B) 2014



(C) 2016

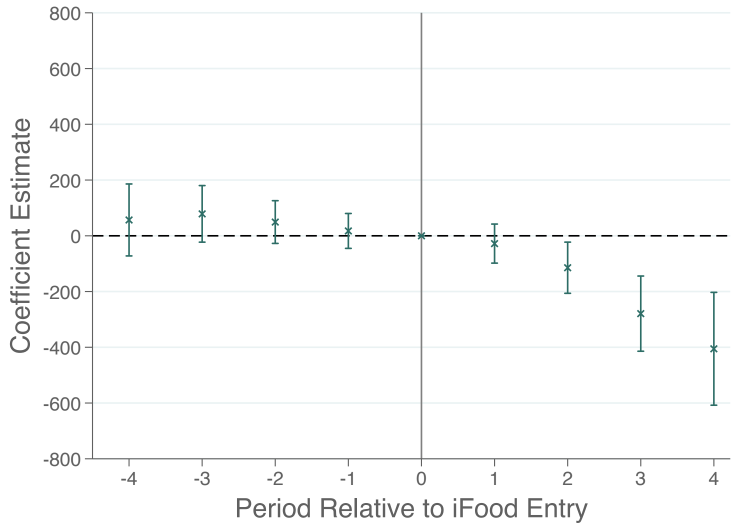


(D) 2018



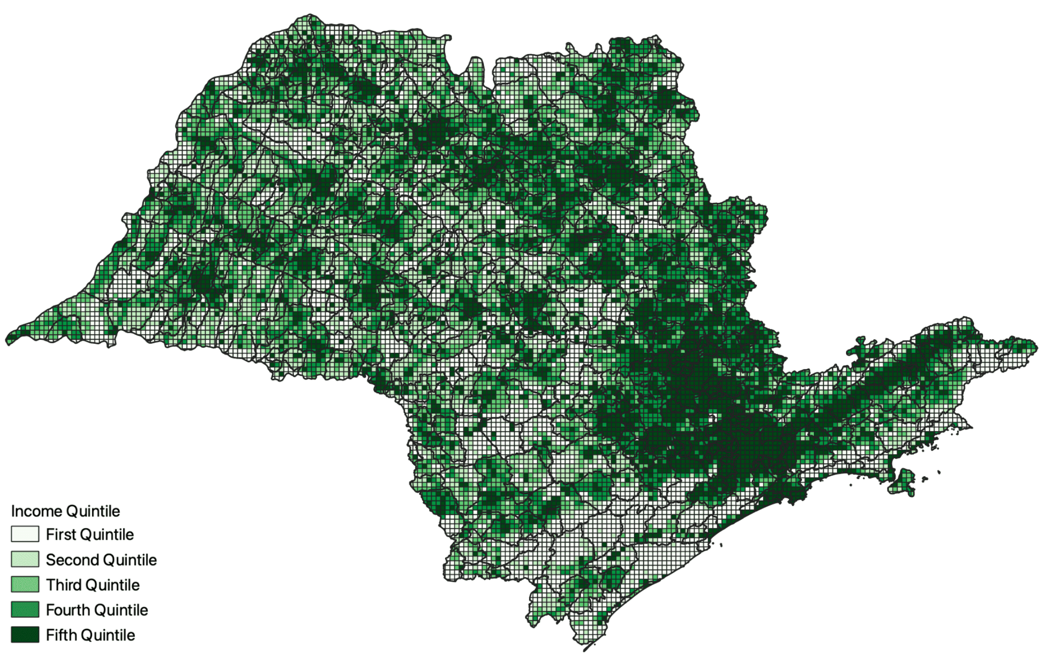
This figure shows the municipalities that have iFood services in 2012 (Panel A), 2014 (Panel B), 2016 (Panel C), and 2018 (Panel D).

Figure A5: Event Study Accounting for Staggered Rollout



This figure shows dynamic treatment effects over time estimated using the method proposed in Callaway and Sant'Anna (2021). The sample is all ever-treated 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: São Paulo State Divided into Grid Cells and Shaded According to Income per Capita



This figure shows a map of São Paulo state divided into 0.04° by 0.04° grid cells and shaded according to quintiles of income per capita. Darker shades represent richer grid cells.

Table A1: Effects by Severity of Crime

	Dependent Variable is **Count of**	
	Non-violent crime	**Violent crime**
	(1)	(2)
Post iFood (=1)	-0.180***	-0.052**
	(0.033)	(0.024)
Municipality Fixed Effects	yes	yes
Year Fixed Effects	yes	yes
Dependent Variable Mean	1938	2540
Observations	1,350	1,350

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 A2: Spillover Effects on Crime in Neighboring Municipalities

	Dependent Variable is **Crime (count)**		
	(1)	(2)	(3)
Neighbor's Post iFood (=1)	-0.034	-0.032	-0.008
	(0.076)	(0.071)	(0.078)
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	-	-
Year Fixed Effects X Pre-period log GDP/Capita		yes	-
Year Fixed Effects X Pre-period log Population		-	yes
Dependent Variable Mean	47	47	47
Observations	2,860	2,860	2,860

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 all columns. "Neighbor's Post iFood" is a binary variable that equals zero before iFood is introduced in any municipality that shares a border with the municipalities in the sample, and one once at least one neighboring municipality receives 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 (the log of) pre-period population, respectively. Standard errors are clustered by municipality. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A3: Effects on Crime by Location and Type of Item Stolen

	Dependent Variable is **Count of Crime**			
	Indoors	**Outdoors**	**Indoors & Personal Items**	**Outdoors & Personal Items**
	(1)	(2)	(3)	(4)
Post iFood (=1)	-0.160***	-0.176***	-0.158***	-0.160***
	(0.033)	(0.027)	(0.034)	(0.030)
Municipality Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Dependent Variable Mean	758	2892	536	1351
Observations	1,350	1,350	1,350	1,350

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 criminal offenses carried out outdoors in column 1 and indoors in column 2. In columns 3 and 4, the dependent variable is the count of criminal offenses outdoors and indoors, respectively, that involved the theft of a personal item. "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 A4: 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)	0.026	-0.103***	0.085**
	(0.028)	(0.034)	(0.037)
2nd Quartile Delivery Demand X Post iFood (=1)	-0.093***	-0.158***	-0.038
	(0.029)	(0.042)	(0.038)
3rd Quartile Delivery Demand X Post iFood (=1)	-0.154***	-0.182***	-0.125***
	(0.022)	(0.031)	(0.026)
4th Quartile Delivery Demand X Post iFood (=1)	-0.214***	-0.257***	-0.186***
	(0.033)	(0.041)	(0.031)
p-value, Q1=Q4	< 0.000	< 0.000	< 0.000
Time of Day Fixed Effects	yes	yes	yes
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Dependent Variable Mean	137	38	99
Observations	32,160	32,160	32,160

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 violent offenses in column 2, and the number of non-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 belong 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 A5: 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)	-0.009***	-0.146***	0.039
	(0.028)	(0.032)	(0.031)
2nd Quartile Delivery Demand X Post iFood (=1)	-0.142***	-0.183***	-0.110***
	(0.027)	(0.033)	(0.030)
3rd Quartile Delivery Demand X Post iFood (=1)	-0.177***	-0.191***	-0.161***
	(0.027)	(0.028)	(0.029)
4th Quartile Delivery Demand X Post iFood (=1)	-0.217***	-0.267***	-0.190***
	(0.037)	(0.038)	(0.033)
p-value, Q1=Q4	< 0.000	< 0.000	< 0.000
Time of Day Fixed Effects	yes	yes	yes
Municipality Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Dependent Variable Mean	137	38	99
Observations	32,160	32,160	32,160

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 violent offenses in column 2, and the number of non-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.