The impact of sharing economy on urban crime

Universidad del Rosario

Facultad de economía

Maestría de economía y Maestría de economía de las políticas públicas

TESIS

Presentada por:

Sara Restrepo Tamayo

Dirida por:

Juan Fernando Vargas
Mauricio Villamizar

Bogotá, Colombia
2019

El impacto de la economía colaborativa en el crimen urbano

Sara Restrepo*

Tesis maestría en Economía y Economía de las Políticas Públicas
Asesores: Juan Fernando Vargas and Mauricio Villamizar

Abstract

La reducción de la delincuencia urbana es una preocupación política primordial en todo el mundo. Los gobiernos han implementado una amplia variedad de programas para controlar el crimen, que van desde la vigilancia policial de los puntos calientes hasta los trabajos de transición para ex convictos. En las últimas décadas, la economía colaborativa, donde las personas comparten o alquilan bienes personales como automóviles o casas, ha ganado importancia como uno de los caminos más accesibles para que los trabajadores poco calificados tengan un ingreso regular. Este documento examina el impacto de una de las compañías de economía colaborativa más grandes de América Latina (*Rappi*) en el crimen urbano en Bogotá. Al usar un modelo dinámico de diferencias en diferencias, se encuentra evidencia sugerente de que la llegada de Rappi condujo a una disminución en los robos. Este trabajo contribuye a la literatura sobre las externalidades de la economía colaborativa.

JEL Classification:

Keywords: crimen, ciudad, economía colaborativa

---

*Departamento de Economía, Universidad del Rosario. E-mail: sara.restrepo@urosario.edu.co

The impact of sharing economy on urban crime

Sara Restrepo[*]

Economics MA thesis
Advisors: Juan Fernando Vargas and Mauricio Villamizar

Abstract

The reduction of urban crime is a paramount policy concern worldwide. Governments have implemented a wide variety of programs to control crime, ranging from hot spots policing to transitional jobs for ex-convicts. Over the past few decades, the sharing or peer-to-peer economy-where individuals share or rent personal goods like cars or houses-has gained importance as one of the most accessible paths for low skilled workers to have a regular income. This paper examines the impact of one of Latin America's largest sharing economy company (*Rappi*) on urban crime in Bogota. Using a dynamic differences-in-differences model, I find suggestive evidence that the arrival of Rappi led to a decrease in robberies. This work contributes to the literature on the externalities of the sharing economy.

JEL Classification:

Keywords: crime, city, sharing economy

[*]Economics Department, Universidad del Rosario. E-mail: sara.restrepo@urosario.edu.co

1 Introduction

In the last century, the sharing economy has grown worldwide, and the debate about the impact of this new economy is massive. Platforms like Uber, Airbnb are in the spotlight because they have changed the way of relating to the company. The base of these also called peer-to-peer, companies is that there is no intermediary between the one who offers the good and the one who receives it, beyond a platform. The most visible impact of the arrival of these companies is the reduction of the costs of the services of goods. On average, a trip on a Uber is cheaper than on a regular taxi and, the accommodation on an Airbnb is more affordable than a hotel.

Nevertheless, the consequences of this revolution are spread all over different aspects of the economy (Cohen et al., 2016; Cramer & Krueger, 2016). For instance, Hall & Krueger (2018) introduced the debate of the flexibilization of the labor market. The drivers that use Uber or Lyft platforms are not employees but are more like contractors. They use the platform whenever they want to offer their services as drivers and they got charged for the use of their app. When looking at Airbnb, real estate prices have changed (Koster et al., 2018), even though this was not the main effect one should expect as a result of the arrival of these companies. The first one is supposed to change the mobility and the second one, the short time allocation prices. That is why the study of the externalities generated by the sharing economy is gaining strength of economics. To my knowledge, Edelman & Luca (2014), Greenwood & Agarwal (2015) and Wu & Brynjolfsson (2015) have worked on the side effects of some peer-to-peer companies[1]. This paper aims to get a first look at the impact of these new type of companies and their correlation on urban crime in developing countries. It contributes to the literature that explores the side effects of the sharing economy by presenting some positive externalities associated with these companies.

This article explores the impact of the sharing economy on urban crime. By this regard, the reduction of urban crime is a crucial policy concern worldwide. Governments have implemented a wide variety of programs to control crime, ranging from hot spots policing to transitional jobs for ex-convicts. Sharing economy companies can offer extra income and, maybe, change the preferences of a pivot criminal. Also, there can be a deterrent effect, since there are more persons offering their services through the app and can wait at the same place. It could also happen that, for a particular type of sharing economy company, there are fewer potential victims on the streets since they are staying at home (UberEats, DoorDash, Grubhub, Rappi, Glovo).

In 2015, a delivery mobile application was founded in Colombia :*Rappi.* It offers,

---

[1]Edelman & Luca (2014) explored the discrimination on Airbnb, Greenwood & Agarwal (2015) evaluated the impact of internet matching platforms on the increase in HIV incidence and Wu & Brynjolfsson (2015) on how Google searches to determine the housing prices and sales.

through the cellphone, the option to buy items from different sources and be delivered on the spot in a short amount of time[2]. These models had a great response in Latin American countries because couriers are willing to accept a low payment for the deliveries (between 2,000 and 5,000 COP)[3]. This equilibrium between the consumer and supplier happens because users of these platforms have a lack of time and can pay for the service. *Rappi* is looking to increase the income of low skills workers and to improve the wellbeing of those who order deliveries. Consequently, if there is a reduction in other variables, like crime, then it can be seen as a side effect, an externality.

When *Rappi* was created, it did not have full coverage of Bogotá. This paper exploits the initial lack of coverage by using a Difference-in-Difference (DID) specification between the neighborhoods where *Rappi* had service and where it did not, for the period between 2012 and 2016. As the treatment group increased through time, I use a dynamic DID model, which is based on the event study methodology, to study the impact of *Rappi's* entrance on urban crime (number of robberies reported by month). The entrance of *Rappi* to a neighborhood is explained by the supply of goods, not the demand (supermarkets, restaurants...). Therefore, I control by the number of active enterprises as a proxy of supply. Parallel trends assumption holds after controlling for a set of covariates such as male population between 20 and 34 years, the number of active enterprises, and the square meter cost; thus it can be assumed that these two groups are comparable. In periods prior to *Rappi*,the null hypothesis was that all interaction coefficients were equal to zero, cannot be rejected. Moreover, I use the ever treated UPZ at my main specification to have a treatment and control group more compare.

The results indicate that the implementation of these new sharing companies decreased the number of robberies and homicides. After the beginning of *Rappi*, the number of robberies at a *Localidad* level decreased by 0.12 standard deviations (19 robberies per 100,000 inhabitants inside every neighborhood). On average, the number of robberies in the controlled group was around 311 before January 2015. No effect was found when doing the analysis at the *UPZ* level when using the ever treated or the entire sample. Even though *Rappi* has expanded to almost all the city, by 2016, some of the *UPZ*s and *Localidades* had no service, that is why I also use a dynamic DID specification using only those *UPZ*s that were treated, at some point [4].

Finally, I also do an analysis by the percentage of parks in each neighborhood, and I found that there is no differential effect in *Localidades* or *UPZ*. Three potential mecha-

---

[2]It is good to note that Rappi offers the option of doing any kind of favor the client might need, this is called *rappi favor*. This option is widely used.

[3]Exchange rate for March 2019 was approximately 1 USD = 3,100 COP.

[4]Besides, in order to be able to talk about causal inference, the treatment effect needs to homogeneous and stationary. However, this is not the case, since wealthier neighborhoods use *Rappi* more and there is a learning effect (the first month, *Rappi* will not be used as much as in the later months of my sample for treated neighborhoods). This is presented in Appendix B.

nisms can explain my results: substitution in the pivot criminal between committing a crime and using *Rappi* mobile application following an economic decision; the presence of more couriers in the neighborhoods; and the presence of fewer people on the streets as they will be ordering deliveries.

This paper proceeds as follow: Section 2 describes the related literature. Section 3 presents the data used for the analysis and Section 4 the empirical methodology. Section 5 displays the results and the potential mechanisms and Section 6 concludes.

2   Related Literature

Becker (1968) and Ehrlich (1973) suggest that individuals rationally weigh the expected costs and benefits of engaging in criminal activity to then compare them with legal activity. Thus, when the elasticity of supply to crime is high (Freeman, 1999) , economic incentives play an important role especially in legitimizing employment in the labor market. Several authors have studied crime from this perspective. For example, Dell et al. (2018) and Dix-Carneiro et al. (2018) used variation from trade-shocks to present area-based evidence of the relationship between local economic factors and criminal activity. Also, Blattman & Annan (2016) studied how the randomized rehabilitation and work-training of high-risk ex-fighters leads to more legitimate employment and less illicit activity in war-stricken Liberia. Pinotti (2015) shows that immigration legalization in Italy led to a drastic reduction in crime, demonstrating that formal sector work leads to less crime. Furthemore, Khanna et al. (2018) found that after the implementation of a law that rose the barriers of formal work, crime increased in Medellin, Colombia.[5]. Using a regression discontinuity design in a subsidy that represents a high cost of formal work in Colombia, they established a causal link between formal employment and participation in organized crime.

Besides the economic variables that modify the decision of committing a crime, Brantingham & Brantingham (1993, 2013) found that some location considerations are taken into account by criminals. Research on the distribution of crime suggested that crime is strongly correlated to aggregate elements of the perceived physical environment: nodes, paths, edges, and environmental backcloth. This relation is mediated through individual awareness and action spaces; therefore, physical environment influences criminal behavior[6]. The individual crime event takes place in a setting sought

---

[5]The decrease in formal employment after the health subsidy was established (Law 100) has also been shown by Camacho et al. (2013), García et al. (2016), among others.

[6]People who commit crimes know a city mostly from legitime routine activities and seem to restrict most of their criminal behavior to these legitimately known areas ((Reppetto, 1974; Carter & Hill, 1979; Maguire & Bennett, 1982; Rengert & Wasilchick, 1985).

by the offender, a place where that person feels comfortable or confident of what will happen. Thus, the search process found that a suitable target is not random, but seems to involve targets near the criminal's usual travel path between major routine activity nodes: home, work, school, shopping malls, and among others. Research made by Walsh (2017), Carroll & Weaver (1986), Gabor et al. (1987) seemed to point to environmental elements that give the offender the feeling that he or she belongs to the setting and does not stand out.

Additionally, Lammers (2017) showed that offender groups are significantly more likely to commit crimes in areas known to multiple offenders in the group (the shared awareness space[7] of the group) than in areas known to only one offender or none of them. Moreover, results of multiples studies showed that criminals tend to offend near their current and previous homes (Bernasco & Nieuwbeerta, 2004; Bernasco & Kooistra, 2010; Bernasco, 2010; Baudains et al., 2013; Johnson & Summers, 2015) and their previous location (Bernasco et al., 2015; Lammers et al., 2015). Bernasco & Kooistra (2010) found that many offenses take place close to where the offender lives, and mear its activity nodes[8]. Through the crime pattern theory and the combination of information from police records, the study confirms that offenders who commit robberies, residential burglaries, thefts from vehicles, and assaults are more likely to target their current and former residential areas rather than areas where they never lived[9].

At the same time, Hipp & Kim (2019) argued that different temporal and spatial patterns determine the robberies; therefore, different temporal patterns indicate the possibility of different mechanisms in operation. Using databases from streets in Southern California, they found that the presence of total employees in the surrounding area is associated with a reduced robbery risk during the daytime, but not during the night time. The risk of a robbery is elevated on a high retail segment on weekends during the daytime, and high restaurant segments into the early evening on weekends. Furthermore, the presence of retail and restaurants in the surrounding area, such as shopping districts is associated with elevated robbery risk in the afternoon and well into the evening. Boivin (2018) studied routine activities and crime in Toronto. Its results suggest that there is a positive relationship between crime and population in many tracts; however, they also found empirical support for the opposite proposition that larger populations are at times associated with less crime. This is especially true for areas that receive visits mainly for shopping, school, and work. This shows that crime can be tackled using different strategies and that there is not a clear consensus about the effect of some of the policies established (e.g., an increase of the number of

---

[7]Research crime location choice has focused on two critical nodes in an offender's awareness space: residential locations and the areas where the offender has previously offended.

[8]The activity space is defined as the activity nodes plus the paths frequently visited by the criminals.

[9]IIn section 5, I show that the couriers live where they work; therefore, if they were committing crimes before, those were done in that same area. If a reduction in crime must be perceived, it should be in the area where they live/ work, which happens to be the same.

employees in a specific area).

Sharing (or peer-to-peer) economy has evolved during the 21st century, becoming the latest trend of digital innovation and changing traditional business models. Platforms that offer this are resolving an allocation problem, using information and technology to match supply, underutilized assets or services (e.g., cars, house, labor), and demand from individuals who are willing to pay for those assets or services. Over the last years, the study of these new enterprises has widely increased. Luca (2017) and Horton & Zeckhauser (2016) presented the economy behind the peer-to-peer model, the characteristics and the rise of these online marketplaces. Moreover, Farronato & Fradkin (2018) and Zervas et al. (2017) for Airbnb; Aguiar & Waldfogel (2016) for Spotify; Seamans & Zhu (2013) and Kroft & Pope (2014), Cohen et al. (2016) and Cramer & Krueger (2016) for Uber: have explored the new equilibriums generated between supply and demand among different industries.

One of the potential impacts of sharing economy platforms is the labor market. According to McKinsey[10], roughly 162 million people in the USA and the EU work in the sharing economy. This represents about 20% to 30% of the workforce[11]. Li et al. (2018), using a DID, found that the unemployment rate decreased significantly and that there was an increase in the labor force participation after Uber arrived in the metropolitan areas. Those jobs with low skill requirements and low entry barrier may seem like a viable choice for individuals who cannot find traditional jobs in a competitive labor market.

Finally, there are also studies that have explored the various externality effects of such sharing economy platforms (Edelman & Luca, 2014; Greenwood & Agarwal, 2015; Wu & Brynjolfsson, 2015; Zervas et al., 2017). Sundararajan (2014) argues that sharing-based companies could potentially have significant social and economic implications, including the disruption of long-standing industries and displacement of incumbents. This paper contributes to the externality effects of sharing economy literature, where there is a general lack of consensus regarding its effects.

---

[10]http://www.mckinsey.com/global-themes/employment-and-growth/independent-work-choice-necessity-and-the-gig-economy

[11]Bonciu (2016) argues that more than 119 million people in North America are more or less involved in sharing economy activities.

3 Data

3.1 Crime

Currently, Colombia has a unified system that collects all the reports of crimes committed. This information is gathered by the Police Department *(Policía Nacional)* through the *Sistema de Información Estadístico, Delincuencial, Contravencional y Operativo* system (SIEDCO) by allowing the neighborhood to analyze at the smallest level of aggregation in Bogotá : *Unidades de planeamiento zonal (UPZ)* [12]. Nevertheless, during the analysis period (between 2015 and 2017), this system faced two significant changes.

Before 2015, there were two main crime databases- the first one, SIEDCO, from the Police Department and the second one, the *Sistema Penal Oral Acusatorio (SPOA)* system, from the Attorney General's Office. In 2015, the information collected through the SPOA system also started being published at SIEDCO. In 2017, a new data methodology was implemented :*A denunciar*. This new platform allows victims to report crimes online. These two changes virtually increased the number of reports, as shown in Figure 1. Nevertheless, this does not mean an increase in the number of crimes committed.

Figure 1: Number of crimes reported at the SIEDCO system
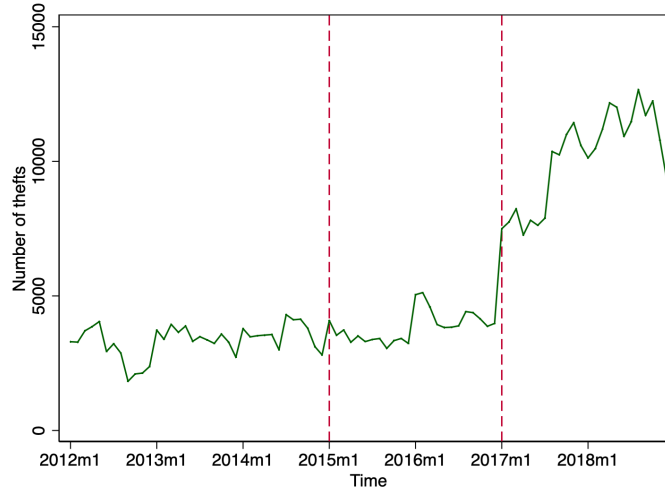
Note: The figure shows the number of robberies reported at the SIEDCO system. The first red vertical line represents the inclusion of the SPOA information to the SIEDCO system (January 2016), the second one (January 2017) represents the implementation of the new system *A denunciar*, which allows the report through an online platform. Source: Data provided by SIEDCO.

---

[12] Bogotá is the capital of Colombia. The urban zone consists of 249 neighborhoods (*UPZ*), divided into 20 *Localidades*. The analysis is at a *UPZ* level and *Localidad* level (which is more aggregated than *UPZ*)

I am assuming that the first shock (2015) affects all the *UPZ* or *Localidades* in the same way. The DID estimator resolves this issue. Despite of that, the second shock (2017) does not affect all *UPZs* or *Localidades* in the same way, because *A denunciar* is an online platform where anybody can report a crime. Access to the internet is not homogeneous across all the *UPZ*. *UPZ*s that are in my treatment group have greater access to this service, thus increasing the number of reports. In 2017, the percentage of reports made in the treatment and control groups were around 51.23% and 37.61%, respectively. This difference is significant at a 99% confidence level[13].

Figure 2 presents the distribution of crime by *UPZ* and *Localidad* for January 2018. This measurement is normalized, and the interpretation is the number of reported robberies per 100,000 inhabitants in the neighborhood (*UPZ* or *Localidad*). As shown, when normalizing crime by the population, robberies seem to concentrate where *Rappi* arrived. Between January 2016 and 0ctober 2016, a randomized experiment took place in Bogotá. Blattman et al. (2018) took 1,919 hotspots streets and increased the time of police officers on those streets. This could affect my main results as it happened at the same time as my analysis (2016).

Nevertheless, as shown in Figure 12, the streets treated were all over the city. Even if there were more streets treated in the East, *Rappi* arrived at this location in 2015 before the intervention. Besides, when analyzing the point estimates, there is no evidence of a substantial decrease in the number of robberies (Figure 8). Therefore, these demonstrate that the effect was homogeneous across the *Localidades*.

---

[13]This data was provided by Bogotá Security Department.

Figure 2: Number of thefts at *UPZ* and *Localidad*

(a) UPZ level January 2016

(b) Localidad level January 2016
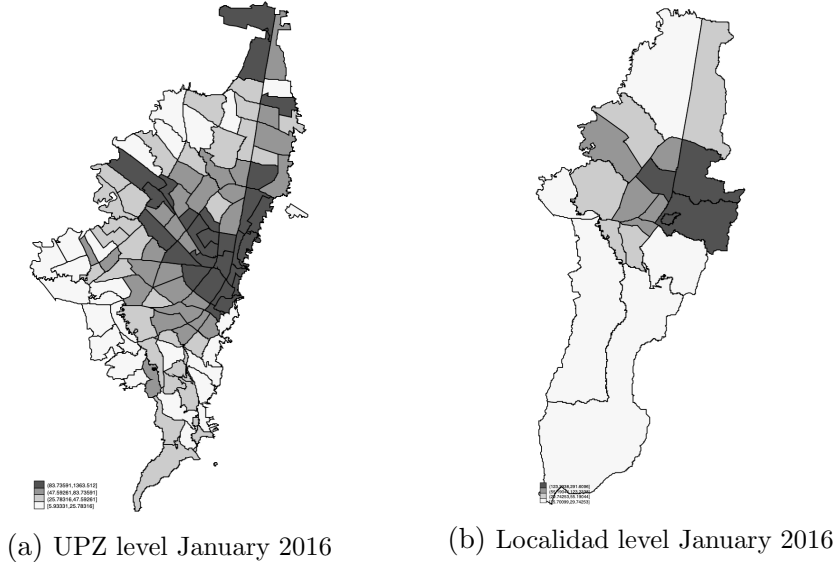
Note: The figure shows the number of reported crimes (thefts) per 100,000 inhabitants in *Localidades* in 2016. Source: Data provided by SIEDCO (2018)

3.2   Courier Data

The use of information from *Rappi* has helped identify the dynamics of couriers in Bogotá. Founded in 2015, *Rappi* allows people to request products from different stores (supermarket, restaurants, and random deliveries) delivered in a short period. In September 2018, it reached a billion dollar value, turning into the first Colombian Unicorn company. Another part is that entry barriers for couriers are low. Couriers only need a bicycle, a cell phone with a data plan, and 80,000 COP to buy the bag to carry deliveries. They are no formal workers for *Rappi*. Instead, they are contractors. Therefore they do not lose their subsidies in case of having one[14]. Figure 3 shows the number of couriers using the mobile application. As shown below, the number of couriers has mostly grown in the past couple years[15].

In Colombia, there are other three leading delivery companies: *Uber EATS*, *Domicilios.com*, and *Mensajeros Urbanos*. The first began its operations in Colombia in 2016; the second one in 2010, and the last one in 2014. Nevertheless, these last two

---

[14]80,000COP = 25.8 USD. Even though Rappi does a screening on the criminal record, the number on non accepted couriers is very low. This measure was adapted more rigorously in the last year.

[15]Even though I am not working with the information after December 2016, the number of couriers working with Rappi mobile application increased to almost 9000 in Bogotá by the end of 2018.

companies are tiny. The largest part of the market is covered by *Rappi* and *Uber EATS*, with *Rappi* being the largest of them all. Therefore, the effect on crime can be mainly attributed to *Rappi*.

Figure 3: Number of couriers working with Rappi app in Bogotá
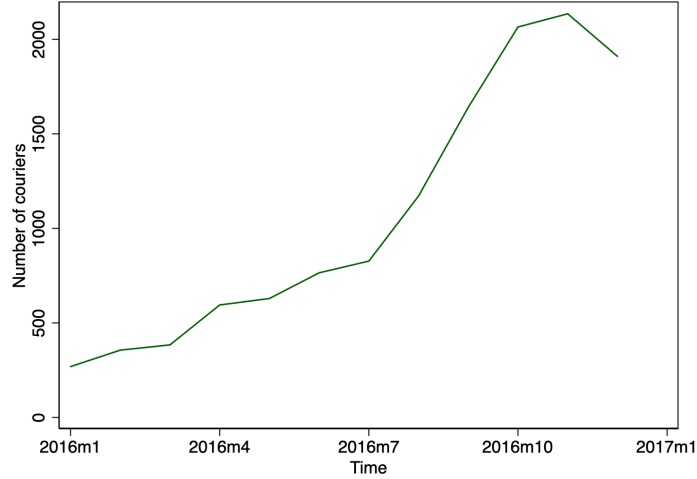
Note: This figure shows the number of couriers using Rappi mobile application. Source: Data provided by Rappi (2018).

In order to define if *Rappi*'s couriers work near their homes, the couriers home address were obtained to analyze the correlation. I have the address reported by each courier and the number of deliveries made in total at each *Rappi-zona*. I matched these *Rappi-zonas* with the Localidades and UPZ to be able to compare the density of couriers[16]. Figure 9 and Figure 10 from the Results section shows the number of deliveries by *Localidad* and *UPZ*. Figure 4 presents the evolution of the number of deliveries made in Bogotá from mid-2015 to 2018 for *Rappi*. As shown, the number of couriers has grown mainly in the last couple of years[17].

---

[16]I don't have access to the individual information of the deliveries; thus, I cannot calculate the average time spent on the bike or the number of kilometers that a courier can drive in one day. Nevertheless, Rappi data science team gave the average they have calculated for the city of Bogotá

[17]Even though I am not working with the information after December 2016, the number of deliveries made using Rappi mobile application increased to almost 1,500,000 by month by the end of 2018.

Figure 4: Number of deliveries made by Rappi in Bogotá
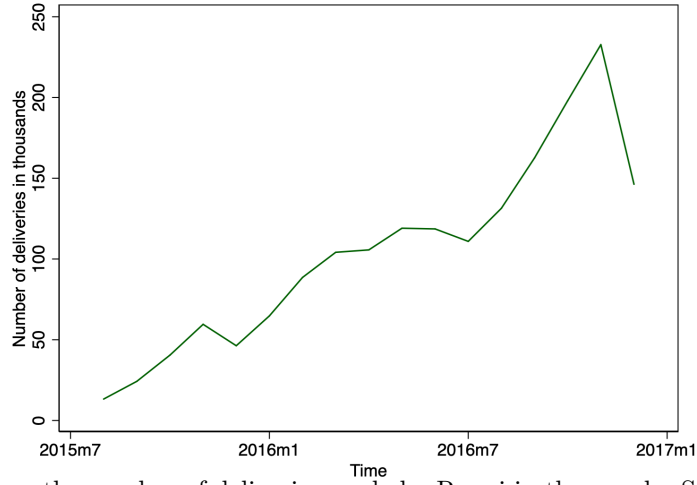
Note: This figure shows the number of deliveries made by Rappi in thousands. Source: Rappi (2018).

Table 1 presents the median, standard deviation, minimum, maximum, and number of observations for earnings, number of deliveries, and average number of months that couriers use the service. The average monthly earning by courier is 134,803 COP. Couriers that use the Rappi app make 95.13 deliveries per month on average, and work for around 9 months using this platform. The analysis of the median showed the earnings decrease to 49,400 COP while the number of deliveries decreased to 26 and the months working with the application down to 6.

Table 1: Descriptive variables

Variable	Observations	Median	Std. Dev	Min	Max
Rappi	12,746				
Earnings		49,400	180,755.5	1,900	1,383,200
Number of deliveries		26	95.13	1	728
Months working with the application		6	8.04	2	36

Note: The couriers that did just one delivery were dropped.The information presented is in COP (colombian pesos). Source: Data provided by Rappi (2018).

Finally, Figure 5 shows the treatment and control groups when analyzing the data at *UPZs* level and Figure 6 at *Localidad* level. The control group takes into account the first places where *Rappi* arrived. In the first case (a) there were 6 *UPZ* in my treatment group and 106 in the control group. Between September 2015 and April 2016, the treatment group increased to 11 and control group to 101.After that, from May 2016 to October 2016, there were 35 *UPZ* in the treatment group, and from the

11

period between November 2016 to August 2017 just one *UPZ* was added to the Rappi zones. For *Localidades*, between May 2016 and August 2017, almost half of the city had *Rappi* services. Therefore, there were 9 *Localidades* treated and 10 in the controlled group [18].

Figure 5: Treatment and control groups evolution through time at *UPZ* level

(a) Beginning - Sept 2015

(b) Sept 2015 - April 2016

(c) May 2016 - October 2016

(d) November 2016 - August 2017

---
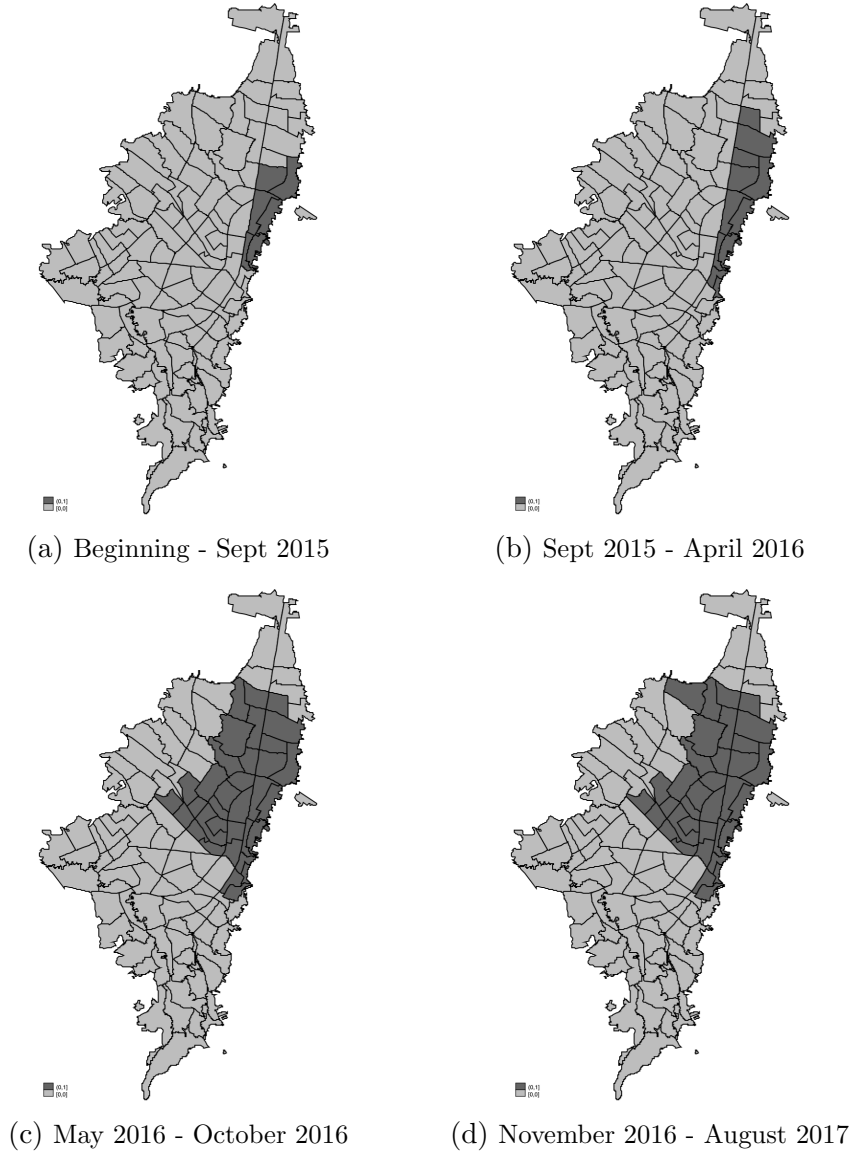
[18]Even though my analysis goes up to December 2016, Rappi has expanded over the last years and in 2018, 18 out of the 19 *Localidades* had access to Rappi services; for *UPZ* the ratio is 79 out of 117

Figure 6: Treatment and control groups evolution through time at *Localidad*

(a) Beginning - Sept 2015

(b) Sept 2015 - April 2016

(c) May 2016 - August 2017
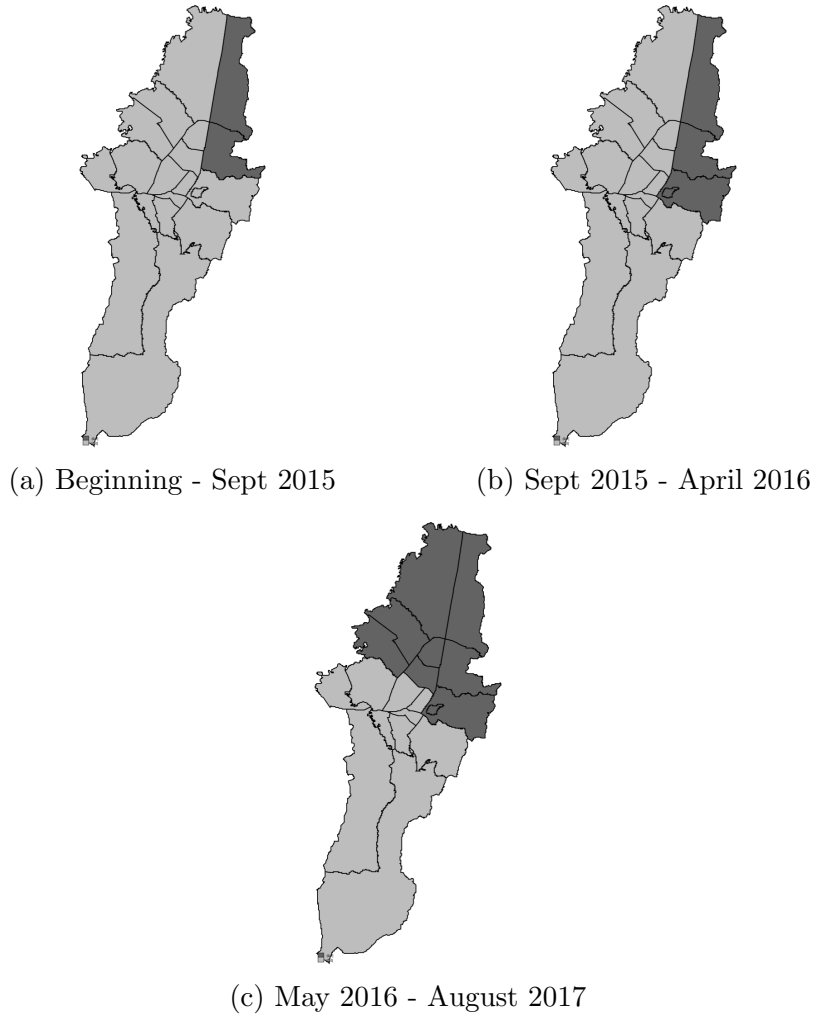
Source: Data provided by Rappi (2018).

3.3   Control Variables

In addition to all the data, some control variables were included. There are external factors that can explain the decrease or increase in the number of crimes committed in a city. Even though I am controlling by location and time fixed effects, some variables can change between the *UPZ* or *Localidades* and through time; thus, they must also be included as controls. These control variables are the number of active enterprises and

male population between 20 and 34 years old[19] and square meter cost of new buildings in Bogotá.

Table 2 and Table 4 present the control and outcome variables at *UPZ* and *Localidad* level of the empirical exercise. The table shows the difference of means, between treated and control groups, before treatment, from January 2012 up until January 2015. As shown, values are statistically significant in almost all cases, which proves pre-existing differences between both groups. Table 3 presents the descriptives of the number of robberies and the controls for the ever treated data sample. In comparison with Table 2, this control and treatment group are more similar than the one using UPZ that were never treated before December 2018 (the entire sample).

Table 2: Differences in Means: Control versus Treatment at *UPZ* level

	Mean Treated	Mean Control	Diff	t	$\Pr(\mid T \mid > \mid t \mid)$
Treatment and control using May 2016- August 2017 delimitation					
Number of reported robberies per 100 000 inhabitants	168.053	75.624	92.429	12.759	0.000
Number of reported robberies	40.112	27.204	12.908	14.302	0.000
Number of enterprises per 100 000 inhabitants	13,193	6,519	6,674	10.374	0.000
Number of enterprises	3,906	3,221	685	6.096	0.000
Male population between 20 and 34 years old per 100 000 inhabitants	14,218	14,000	218.229	2.392	0.017
Male population between 20 and 34 years old	6,423	12,000	-5300	-23.886	0.000
Square meter cost in million COP	2.015	1.141	0.873	27.168	0.000

Note: This table is done with the treatment and control group of May 2016- August 2017. Author's calculations.
Sample period covers January 2012 to January 2015.

Table 3: Differences between Means: Control versus Treatment for *UPZ* that were ever treated

	Mean Treated	Mean Control	Diff	t	$\Pr(\mid T \mid > \mid t \mid)$
Treatment and control using May 2016- August 2017 delimitation					
Number of reported robberies per 100 000 inhabitants	168.053	100.205	67.848	7.827	0.000
Number of enterprises per 100 000 inhabitants	13,000	9,057	4,135	5.531	0.000
Male population between 20 and 34 years old per 100 000 inhabitants	14,149	14,000	149	1.493	0.136
Square meter cost in million COP	2.015	1.075	0.940	35.150	0.000

Note: This table is done with the treatment and control group of May 2016- August 2017. Author's calculations.
Sample period covers January 2012 to January 2015.

---

[19]Khanna et al. (2018) showed that the 63% of criminals captured in Medellín in 2011 were young male. Gronqvist (2013); Kling (2006) focused on the this population for similar reasons.

Table 4: Differences between Means: Control versus Treatment at *Localidad* level

	Mean Treated	Mean Control	Diff	t	$\Pr(\mid T \mid > \mid t \mid)$
Treatment and control using May 2016- August 2017 delimitation					
Number of reported robberies per 100 000 inhabitants	513.431	311.770	201.661	8.403	0.000
Number of reported robberies	1,145.838	935.497	210.341	4.478	0.000
Number of enterprises per 100 000 inhabitants	10,908	6,536	4,372	8.211	0.000
Number of enterprises	23,000	17,000	6,014	7.676	0.000
Male population between 20 and 34 years old per 100 000 inhabitants	14,096	14,000	95.592	1.643	0.101
Male population between 20 and 34 years old	55,000	59,000	-4,000	-1.200	0.231
Square meter cost in million COP	1.630	0.754	0.876	25.055	0.000

Note: This table is done with the treatment and control group of May 2016- August 2017. Author's calculations.
Sample period covers January 2012 to January 2015.

4   Empirical Methodology

As stated in Colonelli & Prem (2017), the treated and control units change throughout time. To deal with this,it is essential to follow the identification strategy of dynamic Difference-in-Difference (DID) model. This model allows for the treatment and control groups to vary across time, creating a contemporaneous control group. This group is composed by two types of units, the units that were never treated and the units that were treated at a later time. In order to address potential problems due to a lack of comparable treatment and controlled groups, I am only using UPZ that were treated before December 2016. It could be said that UPZ never treated before December 2016 are not the best control group because, somehow, they differ from the treated group more than those that were treated at some point; thus not representing the most suitable control group [20]. This exercise decreases the power (fewer observations) but increases the precision. By estimating non-parametric and parametric event study models I captured the dynamics of crime outcomes relative to the month when *Rappi* start. The basic parametric specification Equation (1) reveals the study of the statistical significance and magnitude of the estimates analysis:

$$y_{it} = \alpha_i + \lambda_t + \gamma\ PostRappi_{it} + \delta\mathbf{X}_{it} + \epsilon_{it}; \qquad (1)$$

where, i and t stand for *UPZ* or *Localidad* and month, respectively, and $PostRappi_{it}$ takes the value of 1 for all the months after the arrival of *Rappi*, 0 otherwise. This variable is always 0 for those locations where this entreprise never arrived (before December

---

[20]This is also taken into account when controlling by the homogeneity and stationarity of the treatment effect (Appendix B).

2016)[21]. γ is related to the conditions that change over time for my spatial units where *Rappi* started, compared to the ones that were added later on and those where the service never arrived. The specification includes *UPZ* or *Localidades* fixed effects (α_i) as well as month fixed effects (λ_t). **X** represents the controls included in the analysis[22]. The treatment assignment is not random, then it is controlled by the number of active enterprises in each neigborhood. In fact, the arrival of Rappi to a neighborhood is explained by the supply of goods, not the demand (supermarkets, restaurants...); thus, the number of enterprises that are active represents a good proxy of this demand[23]. Therefore, after including this variable, it can be inferred that the treatment is randomly assigned. ϵ_{it} are standard errors clustered at the level on the *UPZ* or *Localidad* [24], depending of the unit of analysis. The coefficient of interest is γ which measures the change in crime between our treated and control groups, conditional on the set of location and time fixed effects.

The non-parametric event study is presented in Equation (2):

$$y_{it} = \alpha_i + \lambda_t + \sum_{k=-12}^{k=-1} \mu_k + \sum_{k=1}^{k=12} \mu_k + \delta\mathbf{X}_{it} + \epsilon_{it};\qquad(2)$$

where i represents each *UPZ* or *Localidad* and t stand for months. $\{\mu_k\}$ indicators capture the relative event time indicators, taking value 1 if it is month k relative to the beginning of the enterprise on those *UPZ* or *Localidades*. The variables are always 0 for *UPZ* or *Localidades* that were never treated before December 2016. The window around the event is of two years.

Finally, I study heterogeneous effects based on differential pre-existing characteristics using the following interacted specification[25]:

$$y_{it} = \alpha_i + \lambda_t + \gamma_1\,PostRappi_{it} + \gamma_2 \times Heter_i \times\,PostRappi_{it} + \delta\mathbf{X}_{it} + \epsilon_{it}\qquad(3)$$

---

[21]For the first UPZ specification, when I use the UPZ that were ever treated, the variable has at least one value different from 0

[22]These controls are: male population between 20-34 years, square meter cost in million COP and number of enterprises and are included as an interaction between the pre treatment value (2014) and the time indicators (cohorts).

[23]Information given by *Rappi* data scientist.

[24]As I only have 19 Localidades I cluster using wild bootstrap estimators clusters Cameron et al. (2008) in order to reduce the probability of over-reject the null hypothesis.

[25]For this exercise I use the entire sample to be able to capture a larger sample

where $Heter_i$ is a characteristic of the location unit measured one year before the arrival of Rappi. I use a standardized variable of the percentage of parks in the each *Localidad* or *UPZ* in 2014. This analysis can give me information about the mechanisms. In fact, the reduction in crime might be because there are more people on the same places (parks) waiting for a delivery[26].

5 Results

5.1 Robberies

This section reveals the results for the Dynamic Differences-in-Differences (DID) exercises. Given that the treatment group varies based on the start date of *Rappi* at the *UPZ* or *Localidad*, I use this methodology to analyze its impact on the crime level.

Table 5 displays the results for the *UPZ* level using only the ever treated. As shown, there are no significant results. This means that the arrival of Rappi did not have an impact on the number of robberies per 100,000 inhabitants at the smallest level of disaggregation I have access. It is good to notice that a UPZ is larger than a neighborhood but smaller than a Localidad. UPZs might be really small and this represents a problem in the identification strategy because those that commit pickpocketing can change from one UPZ to the other walking or in a small amount of time. At the same time, the courier, who is usually on a bike, can move between the UPZ in a short amount of time; thus dissipating the potential effect.

Table 6 presents the results for the analyzed period January 2012-December 2016 in the *UPZ*, responding to the four treatment groups presented in Figure 5. Analogously, Table 7 displays the results of the impact on the *Localidades*. As shown, there is no impact when analyzing at the *UPZ* level for the entire sample neither [27]. This analysis also applies to criminals. On the other hand, the results for robberies at a *Localidad* level are statistically significant at a 90% confidence level. The main result for *Localidades* is robberies per 100,000 inhabitants. To be able to compare across all the *Localidades* it is important to take into account the population of each location. Thus, the arrival of *Rappi* decreased the number of robberies reported per 100,000 inhabitants in 0.12 standard deviations, on average (19 robberies per 100,000 inhabitants). These results corresponds to $\widehat{\gamma}$ in Equation (1). These exercises include male population between 20 and 34 years, number of active enterprises and square meter cost in million COP as

---

[26]In Bogotá the Rappi couriers wait in parks for the next delivery, that is why parks is a good variable to see id the effect is done by the presence of more Rappi couriers in those places

[27]This results are when including the controls. The control that increases the standard deviation the most is the number of active entreprises

controls; and *Localidad* or *UPZ* and month time fixed effects. Finally, the standard errors are clustered by *Localidad* using wild bootstrap clustered errors as there are 19 units.

Figure 7 and Figure 8 displays the dynamics of the effects around the begining of *Rappi*. It shows the time indicators' mean and standard deviation ($\{\mu_k\}$) in the non-parametric event study presented in Equation (2) over a two year window, where I normalize the coefficient in the month prior to the start of *Rappi*. In order to identify causal effects on a DID estimation, parallel trends assumption must hold. This means that $\{\mu_k\}$ is expected to be not significant (i.e equal to zero) before $k = 0$. This is what we can observe in Figure 8 for the *UPZ* specification (a) and *Localidad* specification (b).

Table 5: DID results for the number of robberies per 100,000 inhabitants at *UPZ* level with restricted sample

	(1)	(2)
PostRappi	16.13	5.603
	(14.25)	(36.87)
Observations	2,098	2,098
R-squared	0.884	0.889
Controls		✓
Month FE	✓	✓
UPZ FE	✓	✓
Mean control group	100.205	100.205
Std. Dev control group	(245.394)	(245.394)

Note: Number of UPZ taken into account: 78. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, *p<0.1

Table 6: DID results for the number of robberies per 100,000 inhabitants at *UPZ* level with the entire sample

|	(1)	(2)
PostRappi	17.92*	34.93
	(10.48)	(35.26)
Observations	6,439	6,333
R-squared	0.772	0.778
Controls		✓
Month FE	✓	✓
UPZ FE	✓	✓
Mean control group	75.62	75.62
Std. Dev control group	(203.49)	(203.49)

Note: Number of UPZ taken into account: 117. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, *p<0.1

Table 7: DID results for the number of robberies per 100,000 inhabitants at *Localidad* level: Jan2012- Dec2016

|	(1)	(2)
PostRappi	-36.52	-19.88*
	(-102.09 , 31.62)	(-179.80 , -6.58)
Observations	1,140	1,140
R-squared	0.822	0.844
Controls		✓
Month FE	✓	✓
Localidad FE	✓	✓
Mean control group	311.77	311.77
Std. Dev control group	(235.67)	(235.67)

Note: Number of Localidades taken into account: 19. I am using wild bootstrap for the clusters, therefore I report the confidence interval. values in parenthesis are the 95% confidence level Robust standard errors in parentheses: *** p<0.01, ** p<0.05, *p<0.1

Figure 7: Point estimates of number of robberies per 100,000 inhabitants at UPZ that were treated at some point
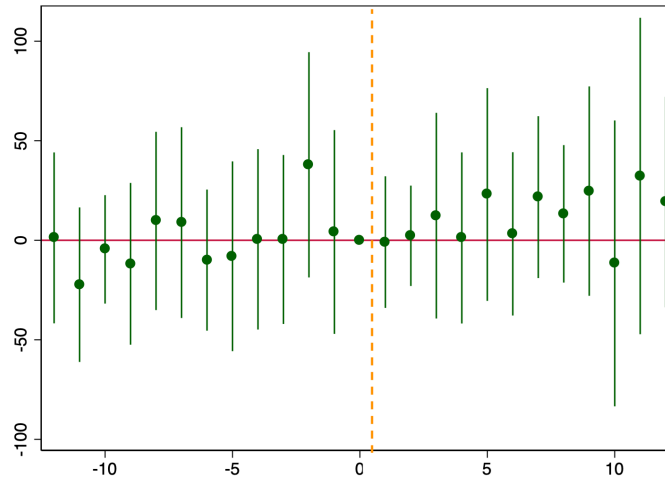
Note: This figure shows the point estimates obtained from the estimation of the main equation limited to only the treated UPZ (not taking into account the never treated). Source: Data provided by Rappi (2018).

Figure 8: Point estimates of number of robberies per 100,000 inhabitants at *UPZ* and *Localidad*
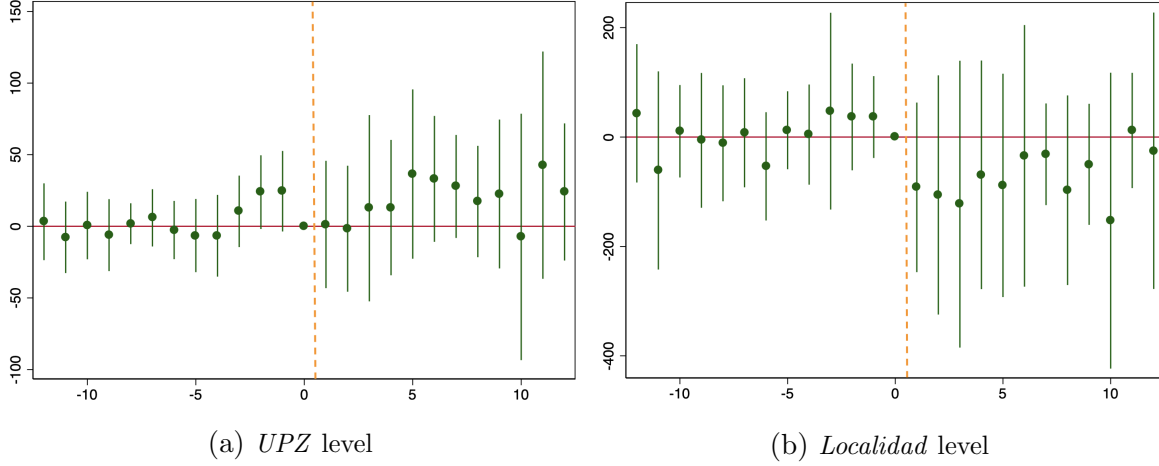
(a) *UPZ* level

(b) *Localidad* level

Note: This figure reports the point estimates obtained from the estimation of Equation (2) together with 99% confidence intervals. The sample covers the window [-12,+12] around the arrival of Rappi. Panel (a) reports the results at a UPZ level and (b) for Localidad.

5.2   Potential mechanisms

Throughout this analysis, the results so far have shown that crime has reduced at the *Localidad* level after the arrival of Rappi. These results do not hold when doing the analysis at a smaller location unit (*UPZ*). These results can occur through different mechanisms. The first one, following Becker (1968), is that the pivot criminal might prefer to do delveries with *Rappi* rather than committing robberies. Moreover, it can be an incapacitation effect since the couriers are doing deliveries during the day, therefore reducing the possibility of committing crimes. In addition, the reduction in crime might be explained by the presence of more Rappi couriers in the neighborhood. As shown in Chalfin et al. (2019), an increase in street lighting can reduce the index crime (7% for the city of New York). Street lighting can also be a proxy of economic activity. More Rappi couriers in neighborhoods can be associated with an increase in economic activity since the couriers wait near delivery hotspots. Finally, the results can show that there are fewer people on the streets since they are ordering more deliveries. This reduction implies less potential victims, and can be shown by the increase in the number of allied stores with Rappi.

For the first mechanism, Camacho et al. (2013); García et al. (2016) showed that, in Colombia, being in the formal sector is very expensive due to the incentives to stay

20

in the informal market (subsidies and conditional cash transfers). As a result, these incentives caused the increase of criminal activity (Khanna et al., 2018) and making crime a potential activity with a higher expected utility. The pivot criminal is changing between committing a crime and doing deliveries. Therefore, there must not be an effect on other criminal activities such as personal injuries and the impact on variables such as homicides must be small or null -some homicides are a consequence of violent robberies. These variables are the reasoning for using the same dynamic DID exercise presented in Equation (1) for personal injuries (Table 8) and homicides (Table 9). The first two columns present the results for *UPZ* and the last two columns for *Localidad.*

It can be seen that there is no impact on personal injuries and that there is a reduction for homicides but only when not taking into account the controls[28] with a 90% confidence level.

Table 8: DID results for the number of personal injuries per 100,000 inhabitants: Jan2012- Dec2016

Variables	UPZ		Localidad	
	(1)	(2)	(3)	(4)
PostRappi	2.953	2.081	0.546	-3.27
	(2.064)	(4.932)	(-15.72 , 16.83)	(-36.66, 29.17)
Observations	6,145	5,971	1,140	1,140
R-squared	0.672	0.699	0.898	0.913
Controls		✓		✓
Month FE	✓	✓	✓	✓
Localidad FE	✓	✓	✓	✓
Mean control group	26.94	26.94	67.97	67.97
Std. Dev control group	(49.39)	(49.39)	(47.00)	(47.00)

Note: Number of Localidades taken into account: 19. Number of UPZ taken into account: 117. I am using wild bootstrap for the clusters when doing the Localidad analysis, therefore I report the confidence interval. values in parenthesis are the 95% confidence level Robust standard errors in parentheses: *** p<0.01, ** p<0.05, *p<0.1

---

[28]In Blattman et al. (2018), they show that the Police-office estimates 5% of murders are consequence of a violent robbery.

Table 9: DID results for the number of homicides per 100,000 inhabitants at *Localidad* level: Jan2012- Dec2016

Variables	UPZ		Localidad	
	(1)	(2)	(3)	(4)
PostRappi	-0.287	-0.669	-12.16**	-39.53
	(0.284)	(0.645)	(-21.94 , -1.84)	(-66.71 , -10.71)
Observations	6,229	6,132	969	839
R-squared	0.555	0.379	0.777	0.826
Controls				✓
Month FE	✓	✓	✓	✓
Localidad FE	✓	✓	✓	✓
Mean control group	2.10	2.10	48.29	48.29
Std. Dev control group	(7.98)	(7.98)	(43.57)	(43.57)

Note: Number of Localidades taken into account: 19. Number of UPZ taken into account: 117. I am using wild bootstrap for the clusters when doing the Localidad analysis, therefore I report the confidence interval. values in parenthesis are the 95% confidence level Robust standard errors in parentheses: *** p<0.01, ** p<0.05, *p<0.1

Moreover, as Brantingham & Brantingham (1993) argue, many people engage in occasional opportunistic crimes. Thus the usual daily activities influence the patterns of criminal activities. Therefore, these crimes concentrate on routine activities, normal activity nodes, and routine travel paths. Cognitive maps and the knowledge of spatial relations influence the crime location.

Figure 9 shows the home location of the couriers by *UPZ*, normalized by its population, in Bogotá as well as their work location (calculated as the number of deliveries by *UPZ* and normalized by its population) . Figure 10 shows the same results at the *Localidad* level. The couriers work and live at the same *Localidad*, as shown in both figures. This can imply that there are no routine travel paths outside their *Localidad*, and therefore if these couriers were committing crimes it would have been inside the same *Localidad*. Besides, according to internal data [29], the average bike commute time is around half an hour and the distance between the store where the product was picked and the delivery is 1.5 kilometers. Moreover, Appendix C presents the results from a small survey answered by 78 couriers that work with Rappi mobile application. More than 15% responded that they lived at the same Localidad where they were working and they reported 42 minutes as the average commuting to work time on bike. On the other hand, it cannot be said that couriers live and work at the same *UPZ*, which might explain the non-significance of the dynamic DID results.

[29]This information was provided by the data scientist of Rappi

Figure 9: Couriers' home address and deliveries at *UPZ* level in 2016
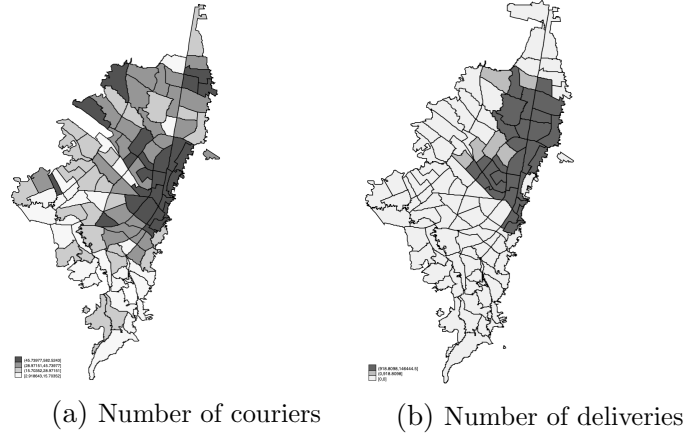
(a) Number of couriers   (b) Number of deliveries

Note: The figure shows the number of couriers and deliveries for every 100,000 in 2016. Source: Data provided by Rappi (2018).

Figure 10: Couriers' home address and deliveries at *Localidad* level in 2016
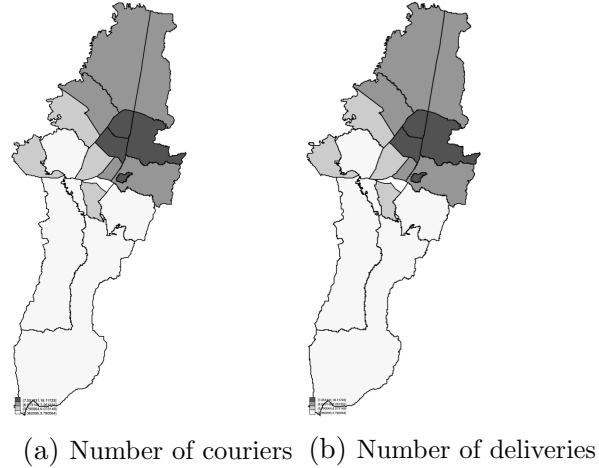
(a) Number of couriers   (b) Number of deliveries

Note: The figure shows the number of couriers and deliveries for every 100,000 in 2016. Source: Data provided by Rappi (2018).

For the analysis of the second mechanism, I did a heterogeneous analysis (eq. (3)) between *UPZ* and *Localidades* comparing areas that had more or less parks in 2014. I create a standardize variable of the percentage of the *UPZ* or *Localidad* cover by a park in 2014. Table 10 column (1) shows that the results are not significant when talking about *UPZ*. This results holds when doing the analysis at a *Localidad* level.

23

Table 10: DID results for heterogeneous analisis at *Localidad* level for robberies: Jan2012- Dec2016

		UPZ
	Localidad	
Variables	(1)	(2)
PostRappi	29.89	-34.86
	(36.20)	(-150.67 , 82.10)
Hetero × PostRappi	-4.679	28.50
	(9.685)	(1.15 , 55.18)
Observations	6,300	1,140
R-squared	0.781	0.826
Controls	✓	✓
Month FE	✓	✓
Spatial FE	✓	✓
Mean control group	75.62	311.77
Std. Dev control group	(203.49)	(235.67)

Note: Number of Localidades taken into account: 19. Number of UPZ taken into account: 117. I am using wild bootstrap for the clusters when doing the Localidad analysis, therefore I report the confidence interval. values in parenthesis are the 95% confidence level. Robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, *$p<0.1$

Finally, for the last mechanism, the increase in the number of deliveries as well as the number of stores that are available in the *Rappi* platform can decrease the number of people on the streets, thus decreasing the probability of being robbed. Figure 11 presents the number of *Rappi*'s allied stores in Bogotá. As shown, the number of stores has widely increased in just one year.

Figure 11: Number of allied stores in Bogotá
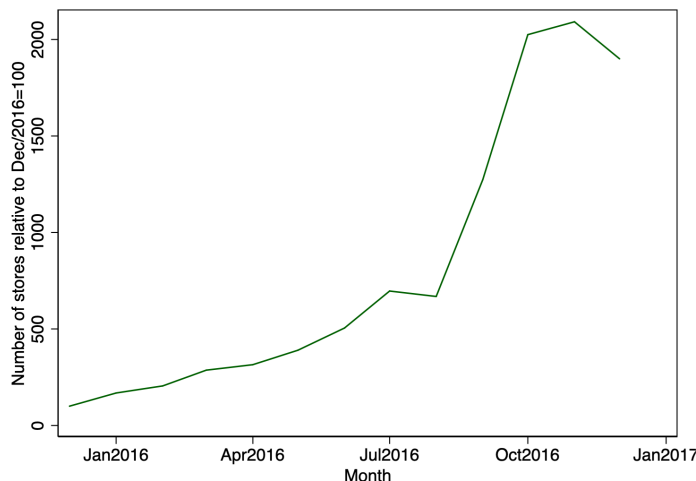
Note: This figure shows the number of stores relative to December 2016 (100) registered in the Rappi mobile application. Source: Data provided by Rappi (2018).

6   Conclusions

Overall, this work aims to present the potential impact of sharing economy companies in developing countries. Using a dynamic DID specification, I found that the arrival of *Rappi* decreases the robberies in 0.12 standard deviations in the largest space location analyzed (*Localidad*). Moreover, there is no effect on personal injuries or homicides. This can be seen as an externality because *Rappi* was created to reduce time spent on errands (demand side) and to offer extra income (offert side); not to reduce or increase urban crime.

I suggest that three main mechanisms can explain this effect. First, following Becker (1968), an economic decision behind committing a crime might exist, therefore, the pivot criminal chooses to use *Rappi* mobile application to do deliveries instead of stealing. In effect, I show that Rappi couriers live at the same *Localidades* where they work (Figure 10). Thus, their nodes are restricted to specific areas (Brantingham & Brantingham (2013)). Secondly, these results can be a consequence of the rise of the number of couriers in some specific places, which reduce the probability of having people by themselves which are easy targets for thieves. In fact, in Bogotá, couriers usually wait in parks for the delivery orders. I use a heterogeneous analysis between *Localidades* and *UPZ* that explores areas with more and less parks in 2014. Nevertheless, the result are not significant. Finally, my main results can be explained by the fact that more people are staying at home. As shown in Figure 11 the number of stores registered in

the platform increased drastically over one year. This could imply that there are fewer people on the streets, thus less potential victims. My results do not hold at a smaller neighborhood level of desegregation (*UPZ*) because the size of the *UPZ* is small; thus it can be possible that it is easy to go across different *UPZ* on the bike and in a short amount of time.

This work contributes to the analysis of the potential side effects of sharing economy. Even though there has been critics on the sharing economy model (Uber, Airbnb, Rappi, etc.), especially on the labor conditions, there might be some side effects that are not being taken into account by the policymakers when changing the regulations. Future extensions could work with georeferenced crime and deliveries. Using buffers, the effect of this kind of companies could be seen in a smaller location unit of analysis, helping with a much clearer identification strategy. Moreover, the couriers' ID could be matched with the Justice Department crime and the subsidies databases allowing a clear Becker (1968) identification strategy.

References

Abraham, S., & Sun, L. (2018). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects.

Aguiar, L., & Waldfogel, J. (2016). *Streaming reaches flood stage: Does spotify stimulate or depress music sales? no. w21653.* National Bureau of Economic Research.

Baudains, P., Braithwaite, A., & Johnson, S. D. (2013). Target choice during extreme events: A discrete spatial choice model of the 2011 london riots. *Criminology*, *51*(2), 251–285.

Becker, G. S. (1968). Crime and punishment: An economic approach. In *The economic dimensions of crime* (pp. 13–68). Springer.

Bernasco, W. (2010). A sentimental journey to crime: Effects of residential history on crime location choice. *Criminology*, *48*(2), 389–416.

Bernasco, W., Johnson, S. D., & Ruiter, S. (2015). Learning where to offend: Effects of past on future burglary locations. *Applied Geography*, *60*, 120–129.

Bernasco, W., & Kooistra, T. (2010). Effects of residential history on commercial robbers crime location choices. *European Journal of Criminology*, *7*(4), 251–265.

Bernasco, W., & Nieuwbeerta, P. (2004). How do residential burglars select target areas? a new approach to the analysis of criminal location choice. *British Journal of Criminology*, *45*(3), 296–315.

Blattman, C., & Annan, J. (2016). Can employment reduce lawlessness and rebellion? a field experiment with high-risk men in a fragile state. *American Political Science Review*, *110*(1), 1–17.

Blattman, C., Green, D., Ortega, D., & Tobón, S. (2018). Place-based interventions at scale: the direct and spillover effects of policing and city services on crime. *Working Paper 23941 http://www.nber.org/papers/w23941*.

Boivin, R. (2018). Routine activity, population (s) and crime: Spatial heterogeneity and conflicting propositions about the neighborhood crime-population link. *Applied geography*, *95*, 79–87.

Bonciu, F. (2016). Impact of the sharing economy on the labor market. *Romanian Economic and Business Review*, *11*(2), 43.

Brantingham, P., & Brantingham, P. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, *13*(1), 3–28.

Brantingham, P., & Brantingham, P. (2013). Crime pattern theory. In *Environmental criminology and crime analysis* (pp. 100–116). Willan.

Camacho, A., Conover, E., & Hoyos, A. (2013). *Effects of colombia's social protection system on workers' choice between formal and informal employment.* The World Bank.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, *90*(3), 414–427.

Carroll, J., & Weaver, F. (1986). Shoplifters perceptions of crime opportunities: A process-tracing study. In *The reasoning criminal* (pp. 19–38). Springer.

Carter, R. L., & Hill, K. Q. (1979). *The criminal's image of the city.* Elsevier.

Chalfin, A., Hansen, B., Lerner, J., & Parker, L. (2019). Reducing crime through envorinmental design: Evidence from a randomized experiment of street lighting in new york city. *http://www.nber.org/papers/w25798*.

Cohen, P., Hahn, R., Hall, J., Levitt, S., & Metcalfe, R. (2016). *Using big data to estimate consumer surplus: The case of uber* (Tech. Rep.). National Bureau of Economic Research.

Colonelli, E., & Prem, M. (2017). Corruption and firms: Evidence from randomized anti-corruption audits in brazil. *Working paper*.

Cramer, J., & Krueger, A. B. (2016). Disruptive change in the taxi business: The case of uber. *American Economic Review*, *106*(5), 177–82.

Dell, M., Feigenberg, B., & Teshima, K. (2018). The violent consequences of trade-induced worker displacement in mexico. *American Economic Review: Insights forthcoming*.

Dix-Carneiro, R., Soares, R. R., & Ulyssea, G. (2018). Economic shocks and crime: Evidence from the brazilian trade liberalization. *American Economic Journal: Applied Economics*, *10*(4), 158–95.

Edelman, B. G., & Luca, M. (2014). Digital discrimination: The case of airbnb. com. *Harvard Business School NOM Unit Working Paper*(14-054).

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of political Economy*, *81*(3), 521–565.

Farronato, C., & Fradkin, A. (2018). *The welfare effects of peer entry in the accommodation market: The case of airbnb* (Tech. Rep.). National Bureau of Economic Research.

Freeman, R. B. (1999). The economics of crime. *Handbook of labor economics*, *3*, 3529–3571.

Gabor, T., Baril, M., Cusson, M., Elie, D., LeBlanc, M., & Normandeau, A. (1987). *Armed robbery: Cops, robbers, and victims.* Charles C Thomas Springfield, IL.

García, J., et al. (2016). Closing the gap between formal and material health care coverage in colombia. *Health and Human Rights*, *18*(2), 49.

Greenwood, B. N., & Agarwal, R. (2015). Matching platforms and hiv incidence: An empirical investigation of race, gender, and socioeconomic status. *Management Science*, *62*(8), 2281–2303.

Gronqvist, H. (2013). Youth unemployment and crime: Lessons from longitudinal population records. *Swedish Institute for Social Research, mimeo*.

Hall, J. V., & Krueger, A. B. (2018). An analysis of the labor market for uber's driver-partners in the united states. *ILR Review*, *71*(3), 705–732.

Hipp, J. R., & Kim, Y.-A. (2019). Explaining the temporal and spatial dimensions of robbery: Differences across measures of the physical and social environment. *Journal of Criminal Justice*, *60*, 1–12.

Horton, J. J., & Zeckhauser, R. J. (2016). *Owning, using and renting: some simple economics of the" sharing economy"* (Tech. Rep.). National Bureau of Economic Research.

Johnson, S. D., & Summers, L. (2015). Testing ecological theories of offender spatial decision making using a discrete choice model. *Crime & Delinquency*, *61*(3), 454–480.

Khanna, G., Medina, C., Nyshadham, A., Tamayo, J., et al. (2018). Formal employment and organized crime: Regression discontinuity evidence from colombia. *Borradores de Economía; No. 1054*.

Kling, J. R. (2006). Incarceration length, employment, and earnings. *American Economic Review*, *96*(3), 863–876.

Koster, H. R., van Ommeren, J., & Volkhausen, N. (2018). Short-term rentals and the housing market: Quasi-experimental evidence from airbnb in los angeles. *CEPR Discussion Papers 13094, C.E.P.R. Discussion Papers*.

Kroft, K., & Pope, D. G. (2014). Does online search crowd out traditional search and improve matching efficiency? evidence from craigslist. *Journal of Labor Economics*, *32*(2), 259–303.

Lammers, M. (2017). Co-offenders crime location choice: Do co-offending groups commit crimes in their shared awareness space? *The British Journal of Criminology*, *58*(5), 1193–1211.

Lammers, M., Menting, B., Ruiter, S., & Bernasco, W. (2015). Biting once, twice: The influence of prior on subsequent crime location choice. *Criminology*, *53*(3), 309–329.

Li, Z., Hong, Y., & Zhang, Z. (2018). An empirical analysis of the impacts of the sharing economy platforms on the us labor market. In *Proceedings of the 51st hawaii international conference on system sciences*.

Luca, M. (2017). Designing online marketplaces: Trust and reputation mechanisms. *Innovation Policy and the Economy*, *17*(1), 77–93.

Maguire, M., & Bennett, T. (1982). *Burglary in a dwelling: The offence, the offender, and the victim*. Heinemann London.

Pinotti, P. (2015). The economic costs of organised crime: Evidence from southern italy. *The Economic Journal*, *125*(586), F203–F232.

Rengert, G. F., & Wasilchick, J. (1985). *Suburban burglary: A time and a place for everything*. CC Thomas Springfield, IL.

Reppetto, T. A. (1974). *Residential crime*. Ballinger Publishing Company Cambridge, MA.

Seamans, R., & Zhu, F. (2013). Responses to entry in multi-sided markets: The impact of craigslist on local newspapers. *Management Science*, *60*(2), 476–493.

Sundararajan, A. (2014). Peer-to-peer businesses and the sharing (collaborative) economy: Overview, economic effects and regulatory issues. *Written testimony for the hearing titled The Power of Connection: Peer to Peer Businesses*.

Walsh, D. (2017). Victim selection procedures among economic criminals: The rational choice perspective. In *The reasoning criminal* (pp. 39–52). Routledge.

Wu, L., & Brynjolfsson, E. (2015). The future of prediction: How google searches foreshadow housing prices and sales. In *Economic analysis of the digital economy* (pp. 89–118). University of Chicago Press.

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. *Journal of marketing research*, *54*(5), 687–705.

Appendix

A   Hotspots Map

Figure 12: Map of hotspots experimental sample
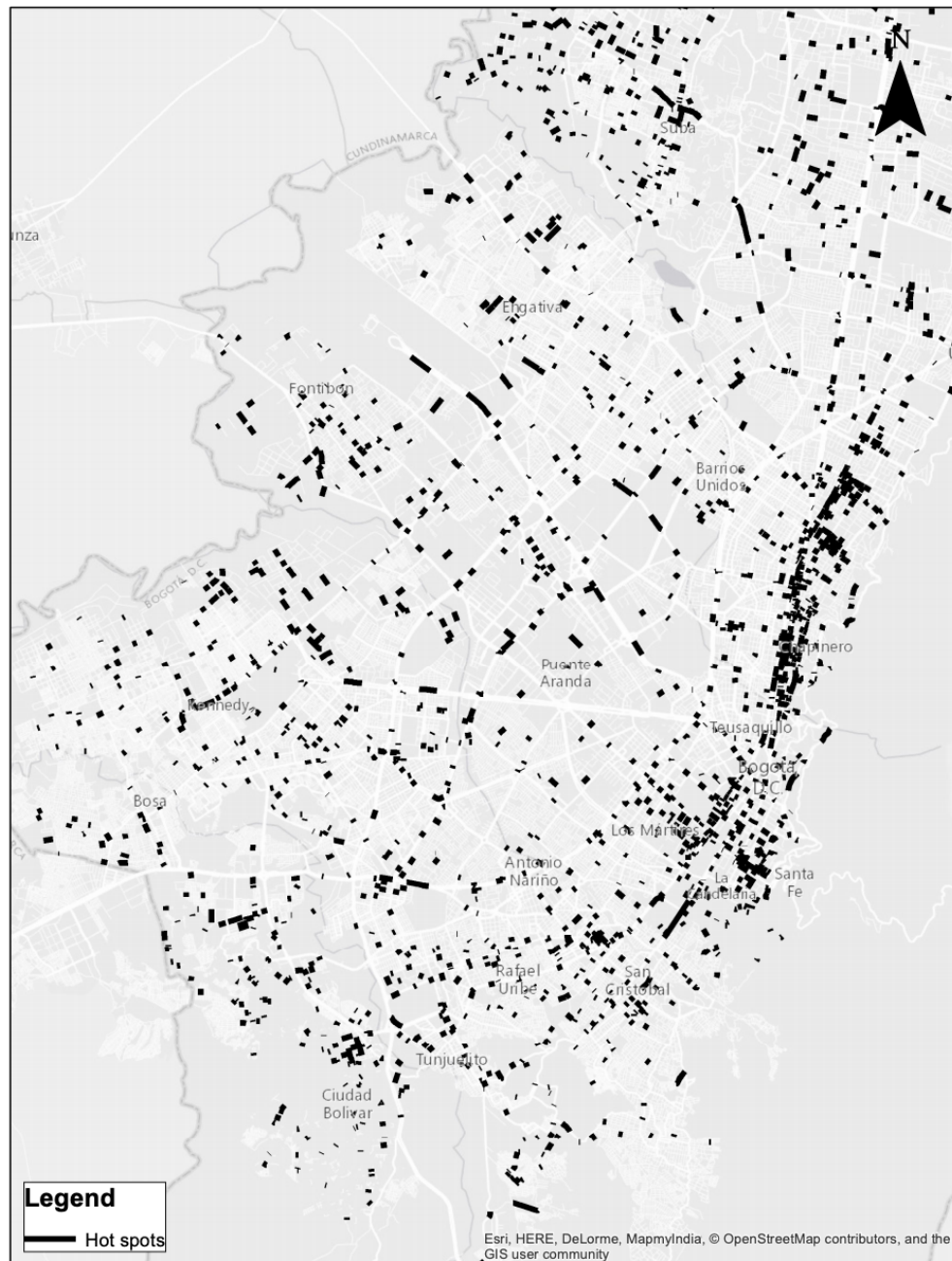
Notes: Experimental street segments, in black, are the 1,919 streets included in our experimental sample.

Source: Blattman et al. (2018)

B Homogeneity and Stationarity of the Treatment Effect

Abraham & Sun (2018) exposed that in fixed effect models where the main regressor is treatment status, the convexity of the treatment effects does not always hold due to the lags and leads of the treatment. In particular, it makes Granger causality test in which coefficients on leads provide evidence for lack of or existence of pre-trends invalid. They propose alternative estimators that are guaranteed to identify convex averages of the cohort-specific treatment effects under heterogeneity. In order to talk about causality when doing an event study model, not only the non anticipatory behavior and parallel trends assumption must hold. The treatment must be homogeneous and stationary. This means the effect must be the same between and within the relative weight ($\{\mu_k\}$ indicators) and location units (*Localidad* and *UPZ*). In this case, there is an intensity associated with the arrival (the first month, Rappi won't be used as much as in the last month of my sample for treated neighborhoods) and there is a heterogeneity associated with the wealth of the neighborhood (wealthy location units will demand more Rappi services than less wealthy locations).

For this exercise, only the unit locations that were treated by the end of the analysis period are taken into account and an interaction-weight is created after saturating a model with all the time fixed effects and weights indicators ($\{\mu_k\}$). Equation (4) presents the saturated model:

$$y_{it} = \alpha_i + \lambda_t + \sum_{e=1}^{T-1} \sum_{l=1-e}^{T-1-e} \delta_{e,l}(\mathbf{1}\{E_i = e\} \cdot D_{i,t}^l) + \epsilon_{it}; \tag{4}$$

where e is the cohort where Rappi arrived to the *Localidad* or *UPZ*, l is the relative time index (weight) and $D_{i,t}^l$ the treatment assignment. This first step, using a linear two-way fixed effects specification, interacts relative time indicators with cohort indicators on $t = 0, ..., T-1$ and $e = 1, ..., T$. Time period T is dropped because everyone is treated in the last period. Cohort 0 is also excluded for the sample because for cohort 0 units when not treated cannot be observed. Secondly, they estimate a set of appropriate weights that is the sample share of each cohort in the relevant period(s). Thirdly and finally, they take those weighted average estimates from step 1 to form average treatment effect estimates with weight estimates from step 2. I added controls in the saturated model and capture the estimates. Thus, cohort average treatment effect estimates, after using Abraham and Sun weights, capture the causal effect of the treatment.

When analyzing the impact of Rappi on urban crime, the treatment is heterogeneous and non-stationary. In fact, there is an intensity associated with the arrival (the first month, Rappi will not be used as much as in the last month of my sample for treated neighborhoods) and there is a heterogeneity associated with the wealth of the neighborhoods. As for the main exercise, I present the estimates of robberies at a *Localidad* level and *UPZ* level. Moreover, Figure 13 presents the dynamic estimators. As shown, all the dynamic estimates, in both *Localidad* and *UPZ*, are not statistically significant. *Rappi* increases the probability of having an informal work, changing the courier's labor decision without losing all the benefits they or their family can receive for being informal.

Figure 13: Point estimates of number of robberies at *UPZ* and *Localidad* level
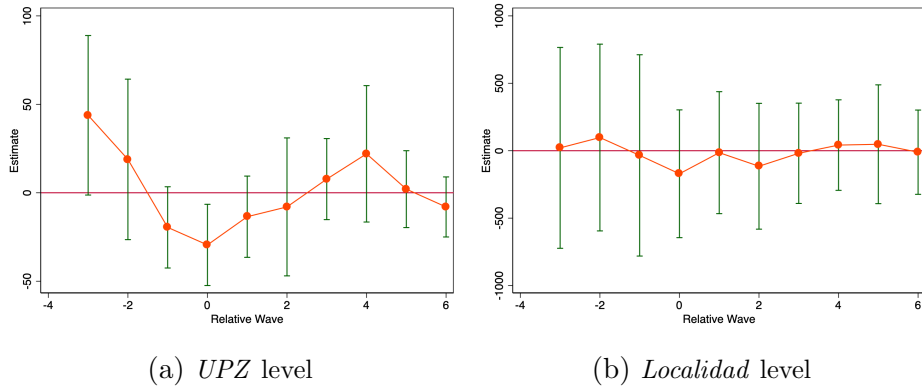
(a) *UPZ* level   (b) *Localidad* level

Note: This figure reports the point estimates obtained from the estimation of Equation (2) together with 99% confidence intervals. The sample covers the window [-3,+6] around the arrival of Rappi. Panel (a) reports the results at a UPZ level and (b) for Localidad.

The results holds when doing the static analysis. Neither *UPZ* nor *Localidad* estimates are statistically significant [30]. This contrast with the results found at *Localidad* level for robberies when doing the standard dynamic DID not taking into account the homogeneity and stationarity of the treatment. Therefore, it cannot be said that there is an impact of Rappi's arrival on the level of crime in Bogotá. As explained before, the treatment effect of the arrival of *Rappi* is neither homogeneity nor stationary. This means that there is a learning effect between the first and the -n month and that there are some location characteristics as the wealth or distance to the stores that generate a difference among the use of the mobile application. This can explain the vanish of the effect when weighting by the number of treated at each cohort.

---

[30]The beta and standard deviation for the UPZ estimate is -137.321 and 137.101, respectively; and -84.443 and 1545.240 for the Localidad estimates.

C   Rappi couriers' surveys

To better understand the dynamics of the mobility of the couriers, I conducted a small survey of 78 couriers who worked in the busiest areas, with the highest demand for orders. This survey asked them about the Localidad where they lived, how much time they spent on a bike going between their houses and the place where they work the most and what they would be doing if they were not couriers.

They spend, on average, 42 minutes commuting. Figure 14 presents the result for the question: "In which Localidad do you live?". As can be seen, more than 15% of the sample reported living in Chapinero. The survey was done in Chapinero; therefore, those couriers work where they live or near to there. Finally, from a qualitative perspective, when asking the couriers "If you were not working with the Rappi application, what would you be doing?" most of them responded a looking for an informal job or asking for money on the streets.

Figure 14: Localidades where couriers live (survey)
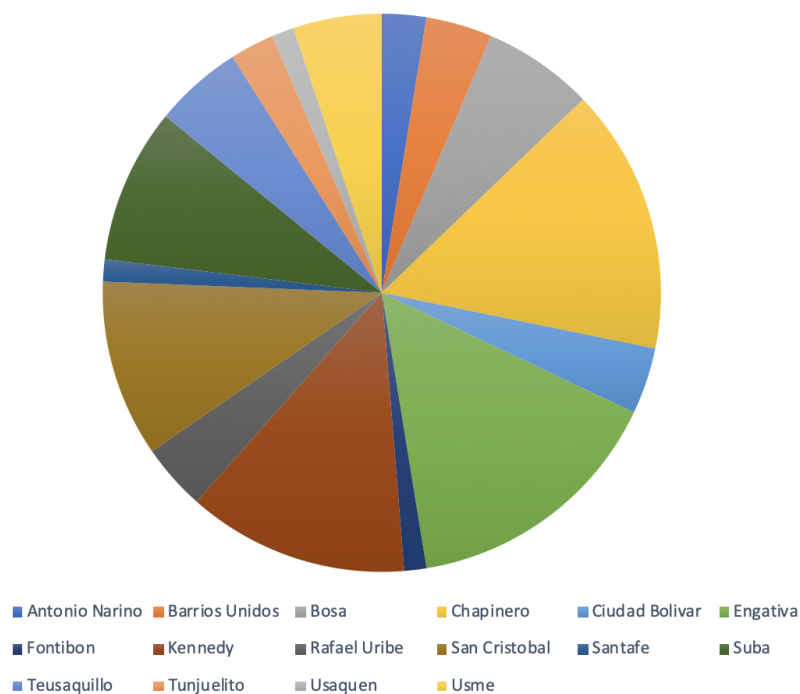
Note: This figure shows the answers to a survey responded by 78 couriers that work with Rappi. The question was: In which Localidad do you live?.