IDB WORKING PAPER SERIES Nº IDB-WP-1108

How Potential Offenders and Victims Interact:

A Case Study from a Public Transportation Reform

Patricio Domínguez

Inter-American Development Bank
Department of Research and Chief Economist

April 2020

How Potential Offenders and Victims Interact:

A Case Study from a Public Transportation Reform

Patricio Domínguez

Inter-American Development Bank

April 2020

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Domínguez, Patricio.
How potential offenders and victims interact: a case study from a public transportation reform / Patricio Domínguez.
p. cm. — (IDB Working Paper Series ; 1108)
Includes bibliographic references.
1. Local transit crime-Chile-Prevention. 2. Victims of crimes-Chile-Attitudes. 3. Local transit-Fares-Chile-Automation. 4. Smart cards-Chile. I. Inter-American Development Bank. Department of Research and Chief Economist. II. Title. III. Series.
IDB-WP-1108

http://www.iadb.org

Abstract[*]

This paper models crime rates as a function of the interaction between potential o enders and victims. In particular, the paper studies robbery of bus drivers, a crime that remains common in cities throughout the world. Exploiting the timing of a significant reform introduced in Chile in the public transportation sector and detailed administrative data on crime incidents, the paper shows how victims' propensity to resist an attack can alter the level and nature of criminal activity. The paper also finds a large decline in crime after the implementation of a technological innovation that eliminated cash transactions on buses. The results suggest a strong relationship between victim's incentives, cash presence, and crime.

JEL classifications: K42, R41
Keywords: Economics of crime, Victims, Cash, Public transportation

[*]Inter-American Development Bank – Department of Research and Chief Economist, 1300 New York Ave NW, Washington, DC 20577. Email: patriciodo@iadb.org. I would like to thank the *Subsecretaria del Delito* and *Ministerio de Transporte* of the Chilean government for providing the data used in this study, and Conicyt for financial support. For important comments on previous versions of this draft, I would like to thank Michael L. Anderson, Juan Pablo Atal, Daniel Baker, Phil Cook, Bill Easterly, Avi Feller, Rucker Johnson, Carola Jorquera, Amy Lerman, Carlos Melo, Juan Carlos Munoz, Steven Raphael, Krista Ruffini, Eugene Smolensky, and seminar participants at Berkeley, the IDB, and the Transatlantic Workshop on the Economics of Crime.

Since the work of Becker (1968) the economics of crime literature has offered remarkable contributions to the understanding of the causes and consequences of criminal activity. Most empirical evaluations focus on the extent to which a particular policy deters or incapacitates potential offenders, and very little attention is paid to the interactions between offenders and victims. This issue was raised many years ago by Cook (1979). Cook, Machin, et al. (2013) define this relationship as an endogenous bidirectional "loop" between victimization risk and private prevention efforts, which "has been largely neglected in the economics literature" (Cook, Machin, et al., 2013, p.10).[1] Within this framework changes in observed crime rates cannot be fully attributed to offenders' actions; they also depend upon the interaction between offenders' choices and the choices made by potential victims.

In this paper, I analyze robberies in the public transportation system, which offers an interesting setup to understand how offenders and victims interact. I develop a simple model of the behavior of potential offenders and victims to lay out possible consequences for aggregate crime rates. The model shows explicitly how variation in victims' propensity to resist an attack modify not only the level of criminal activity but also its characteristics in terms of the level of violence exhibited by an offender. From a broad cost-benefit analysis perspective, this is important since assessments of the social costs of crime based exclusively on realized offenses may hide considerable costs – namely, all protection measures adopted by potential victims in order to minimize their risk of being assaulted or simply reducing the costs of an offense when victimized.

To analyze this relationship empirically, I focus on the robbery of bus drivers, a crime that remains common in cities throughout the world. Such robberies were a salient problem in many cities in the United States in the late 1960s and early 1970s. In this case, the implementation of exact-change fare collection –along with on-board safes into which fares were dropped– has been recognized as a classic crime prevention measure (Smith and Clarke, 2000). Exact-change fare collection systems or alternative efforts to harden the target are still rare in developing countries where the public transportation sector

[1] In a similar vein, Nagin, Solow, and Lum (2015) have recently referred to Cook (1979) as a "valuable and underappreciated work." (Nagin, Solow, and Lum, 2015, p.79)

is lightly regulated and mostly operated by informal and often privately-owned transit companies. For instance, in Santiago, the capital and by far the most populous city in Chile, fare payment using cash was the norm up through 2007.

Typically, in cities where public transportation is lightly regulated cash is the unique payment method, and drivers' salaries are determined on a per-passenger basis that makes them accountable for protecting fare revenues. Drivers use a fare-collection box located next to them to take in cash and distribute change back to passengers. Due to the high liquidity and untraceable nature of cash, the presence of this visible collection of cash offers an attractive criminal opportunity commonly associated with very violent crime incidents in the public transportation system.

I exploit the specific timing of a major reform in the public transit system that both modified driver's incentives to protect the fare collection boxes and subsequently eliminated the use of cash as the payment mechanism. Transantiago was a reform of the public transit system implemented in Santiago, Chile between 2005 and 2007. I use a large administrative database managed by the Chilean police that includes a high level of detail associated with each incident reported in Santiago between 2005 and 2010. These data allow me to identify important details regarding robbery incidents such as the location, the kind of good stolen, the weapon used to threaten the victim, and whether the victim was injured in the attack.

To analyze how a change in the incentives for a victim to resist impacts the level and nature of crime, I focus on a transition period of Transantiago, a period during which new bus companies with an alternative driver compensation structure were introduced into the system. The implementation of Transantiago was delayed by 16 months due to technical difficulties in terms of the bus fleet and the roll out of the debit technology. During the interim period, bus companies were required to modify drivers' compensation from being a proportion of fare revenue to fixed salaries. The reform thus decoupled the take-home pay of drivers from the amount of revenue (net of robberies) turned in at the end of the day. In essence this change can be described as creating a moral hazard situation between bus drivers (agent) and bus operators (principal). Under this new scenario, bus drivers were less likely to adopt costly measures to protect the money collected on each ride since their income was no longer in danger. I find a large increase in cash-related robberies along with a proportional decline in the level of violence exhibited by the offenders, operationalized as the choice between using a gun or knife in the robbery.

I also analyze the effect of a subsequent reform that introduced a simple technological innovation, in which payment with a smart contactless debit card replaced payment with cash on all buses. In particular, I find that robberies sharply decreased after the full implementation of Transantiago in 2007, making public transit safer. I discuss the extent to which it could have been driven by other policies that Transantiago put in place at the same time, although the magnitude of this estimate is very large. I analyze its robustness under different identification strategies. My findings relate to and bolster those of Wright et al. (2014), who noted a decline in street crime in association with a reduction in cash economic transactions. Wright et al. (2014) suggest that a reduction in the use of case in economic transactions can be considered as an alternative explanation of the reduction in crime across Northern and Western Hemisphere democratic nations (Zimring, 2006; Levitt, 2004).

In the following section, I discuss the contribution of this paper along with previous studies that have analyzed the role of victims and the environment in shaping criminal activity. Then I present the alternative empirical approaches I implement. Finally, I present the set of results and discuss some of its implications in the conclusion section.

1 Criminal Opportunity Theory

The economics of crime literature has long emphasized the role of offenders and the extent to which specific mechanisms, such as variation in police presence or staffing levels (Levitt, 2002; Di Tella and Schargrodsky, 2004; Draca, Machin, and Witt, 2011; Chalfin and McCrary, 2013), prison population (Levitt, 1996; Buonanno and Raphael, 2013), or sentencing policies may affect crime. But victim's behavior can also affect the level and nature of criminal activity by taking a variety of actions: a potential victim can harden an attractive target, alter travel behavior to avoid certain areas or being out of the house during certain times of the day, or purchase goods and services that either reduce the likelihood of being victimized or minimize the costs associated with being victimized.[2] The role of victims has not necessarily been unnoticed, but to date has received less scholarly attention, especially regarding empirical applications. Similarly, the role of small changes in the nature of criminal opportunities (for example, the use of cash or the ability to fence stolen items) has also been relatively unexplored, with a few notable exceptions. In this section I review some basic considerations regarding victim behavior and other factors that ultimately determine the stock of potential criminal opportunities and in turn the crime rate.

An important theoretical contribution regarding the role of victims is the work of (Cook, 1979; Cook, 1986).[3] Cook proposes, following Van den Haag (1975), that "the amount of some types of crime may be limited by the number of profitable opportunities to commit the crime, rather than by the number of people who are prone to commit the crime" (Cook, 1977, p.169). A key insight of this approach is the notion of a "feedback loop" governing the manner in which individuals adapt their behavior based on the anticipated consequences. Here, the level of effort exhibited by potential victims to protect their property determines the availability of criminal opportunities, which in turn depends on the level of risk the potential victims perceive. In other words, the degree to which potential victims undertake self-protection measures depends on the perceived risk and costs of victimization.

Among the empirical studies that have focused on victim's behavior and how it modifies the set of criminal opportunities available, Cook and MacDonald (2011) show that actions adopted by private actors can have a substantial effect on crime and crime-control policies. Other empirical studies have focused on how victims can alter the set of criminal opportunities by hardening an attractive target (Vollaard and Van Ours, 2011) or by modifying the nature of the target. Changing the liquidity of a reward can deter criminals from stealing an object. In that sense, changes in cash circulation,[4] as well as

[2]Freeman (1999) guesses that around 0.6 % of U.S. GDP is spent on private crime prevention (taking a taxi instead of walking or locating a business in the suburbs instead of in the center of the city), which accounts for almost a third of the total GDP allotted to crime-control activities. By contrast, Shavell (1991) states that private expenditures on security may even exceed public expenditures.

[3]Other theoretical approaches are: Clotfelter (1977) and Shavell (1991).

[4]The relationship between cash and criminal incentives exceeds the direct reward associated from stealing

the incorporation of tracking devices in cell phones, are commonly cited as practical ways to deter crime. Ayres and Levitt (1998) and Gonzalez-Navarro (2013) analyze slightly different implementations of LoJack devices in the United States and Mexico. Ayres and Levitt (1998) and Gonzalez-Navarro (2013) find reductions in vehicle thefts, but with important consequences in terms of displacement to other areas or car models, based on the observability of the tracking device.

Other scholars have emphasized how interactions between offenders and victims shape the level and nature of crime. O'Flaherty and Sethi (2008), O'Flaherty (2015), and O'Flaherty and Sethi (2010) show that perceptions of race in the United States may account for racial disparities in terms of violent robbery and murder incidents. More closely related to one of the findings on this paper, McClellan and Tekin (2017) and Cheng and Hoekstra (2013) raise serious concern about the ability to increase the level of public safety by encouraging potential victims to resist an attack, as in the case of "stand your ground" laws.

Regarding the particular context of this paper, there is an interesting set of studies in the situational crime prevention literature. Smith and Clarke (2000) present a description of why public transportation offers an interesting setting for analyzing how environmental factors affect crime. A salient case has to do with the sentinel role of bus drivers preventing vandalism (Mayhew, Clarke, and Elliott, 1989). Smith and Clarke (2000) devote special attention to the case of robbery of staff, a particularly important topic in the United States during the late 1960s and early 1970s. During that time robbery of bus drivers, especially robbery of fare revenue, became a serious problem across many cities. The main solution proposed across the United States was the introduction of exact-change fare collection, along with on-board secure boxes into which the fares were deposited (Gray, 1971). The use of these devices was strongly promoted as an anti-crime tool (Gray, 1971), especially after two consecutive shootings of bus drivers, first in Washington D.C., and then in New York in May 1968. Chaiken, Lawless, and Stevenson (1974) highlight

money. Rogoff (2016) argues that the movement to a cashless society may reduce a considerable number of illegal and criminal activities, especially considering that cash provides a medium of exchange that clearly facilitates transactions in the underground economy.

that after the introduction of exact-change fare collection,[5] robberies of drivers dropped dramatically, and interestingly, they also report a subsequent increase in robberies in the subway system.

2 The Implementation of Transantiago

In the early 2000s, ground public transportation in Santiago, Chile was ranked among the city's worst public services. In that context, the government decided to implement a unique modernization of the entire system. A key pillar of the reform was to integrate the underutilized infrastructure of the subway/Metro with a new and improved bus service. As a result, a new payment system was introduced. In addition, the driver's compensation structure changed from being a proportion of daily fare revenues to a fixed amount defined independently of the number of passengers on each particular ride. Transantiago was a highly ambitious plan, and during the first months of fully implementation was criticized harshly by the public due to many issues associated with the design and actual implementation of the policy.[6] In this section, I describe the implementation of Transantiago and the main motivations behind this policy. I pay specific attention to the aspects of the reform that plausibly affected the criminal activity reported on buses, especially regarding robbery incidents.

2.1 Pre-Reform System

The origins of the public transportation system that existed in Santiago prior to the reforms can be traced back to the Chilean dictatorship of the early 1980s, which privatized and deregulated the bus system. While new regulations of bus transit were introduced during the 1990s, the sector was only lightly regulated, and the industrial organization of the bus system was highly atomized. There were around 8,000 buses serving 380 routes with

[5] This report mainly focuses on the impact of police activity on crime in the New York City Subway system. Smith and Clarke (2000) also mention a Stanford Research Institute study (1970) that report similar results in a review of the effect of exact-change fare systems in 18 other cities

[6] For a general description of different aspects associated with the design and implementation of Transantiago see Gómez-Lobo (2007), Muñoz and Gschwender (2008), Briones (2009), Muñoz, Ortúzar, and Gschwender (2009), Olavarrıa Gambi (2013), and Beltrán, Gschwender, and Palma (2013).

more than 3,000 unprofessional/informal operators (Muñoz, Ortúzar, and Gschwender, 2009). Perhaps the most notorious feature of the system was its lack of integration in almost every possible dimension, exemplified by the payment system. Figure 1 shows a typical bus driver's space that illustrates the old payment mechanism. Passengers paid for their tickets with cash inside the bus. On top of having to drive the bus, drivers had to receive cash from each passenger, calculate correct change, and finally provide riders with their tickets. In addition, drivers were responsible for protecting the money collected in the so-called "Peceras" (Spanish for "fish-tank"), a responsibility that bore directly on their pay. Operators paid bus drivers' salaries according to the number of passengers' trips —which should be reflected by the number of tickets issued on each ride. They had no formal contracts and they were "...expected by owners to take about 1/3 of their income by pocketing low "fares" charged to some passengers willing to ride without (a) ticket" (Muñoz and Gschwender, 2008). Hence, bus drivers were fully responsible for the money collected on each route. Considering the way bus routes were designed, this meant that they needed to drive on average 60km before they could do the accounting balance in a safe place. "Peceras" were implemented as open boxes that allowed bus drivers to constantly sort the cash they were receiving and give cash back to their passengers. They often carried sticks or some non-firearm weapon as a personal safety measure against an eventual assault.[7]

The reform effort was driven in large part by the need to modernize the system in a broad sense. The two main problems that were identified were the inefficient structure of bus routes, and a phenomenon known as "the war for the fare," referring to the on-the-street competition for passengers. According to Gómez-Lobo (2007), both problems were associated with the way that operators (bus owners) were compensated in a highly decentralized and atomized system.

The inefficient structure of bus routes was arguably a direct consequence of the lack of system integration and coordination. A single transfer doubled passenger's costs.

[7]Gallagher and Sgarzi (1974) and Pearlstein and Wachs (1982) report that during the 1960s, prior to the implementation of exact change policies in the United States, bus drivers carried arms while driving for self-defense purposes. More recently, Easteal and Wilson (1991) report the use of weapon as one of the self-protection measures implemented by taxicab drivers.

Therefore, in order to make most of demand, operators tended to privilege routes that minimized passenger transfers in the system. As a result, and given the sprawling footprint of the city, the routes of most buses passed through downtown and connected two points of the city's periphery and had an average length of 60 km (Muñoz, Ortúzar, and Gschwender, 2009). This inefficient structure of routes also generated an oversupply of service in highly congested areas, especially downtown. Gómez-Lobo (2007) reports that 80 percent of bus services circulated through the main six avenues of the city, which clearly accentuated the problems of traffic congestion and air pollution.

Furthermore, the on-the-street competition for passengers was a critical problem that directly affected the quality of the service. Among the most notorious issues were passengers' safety (car accidents), and discrimination against high-school students, and the elderly, who paid a subsidized fare. Even more critical from a systemic point of view was that competition for drivers prevented any serious effort to coordinate buses to improve general system performance. Also, considering the highly atomized industrial organization and the way operators were compensated (based on the money they collected on their buses), coordination even across a single line was extremely rare. Drivers within the same line competed against each other, in that they all were attempting to take on the highest number of passengers per trip.

2.2 Transantiago

At the core of Transantiago was the idea that a more integrated system would fix many of the problems discussed above. Muñoz, Ortúzar, and Gschwender (2009) state that the main goal of Transantiago was to increase use of multi-mode public transit (e.g., bus and heavy rail). For this reason, modernization of the bus system was a high priority, in the hope that this would reduce congestion, travel and wait times, and the number of car accidents (Dıaz, Gómez-Lobo, and Velasco, 2004). In addition, the government mandated that the system be environmentally, socially, and economically sustainable. The environmental goal was particularly important, given the high levels of air pollution in Santiago at the time. In terms of the economic sustainability of Transantiago, the government expressed its hope that the system "… would be subsidy-free and charge an average fare similar to that of the previous system" (Muñoz, Ortúzar, and Gschwender, 2009, p.46). The main features of Transantiago were defined as the following:[8]

- New organization of the industry and new routes: It laid out a new bus network with ten feeder and five trunk services. Thus, the previous organization of more than 3,000 unprofessional operators was replaced by a new structure. The city was divided into 15 zones, and all buses were provided by 15 different operators, corresponding to the 15 zones. The entire industry structure was franchised through an international call for tenders in 2004. Each of these "service areas" was to be serviced by a single company that won out in the bidding process. In addition, to minimize the possibility of on-the-street competition, new companies were required by law to pay fixed salaries to bus drivers.

- A modernized bus fleet: Companies were required to put new buses into service gradually. Unlike the old buses, the new vehicles were equipped to service riders with disabilities and could accommodate more passengers. Also, since the system was in theory designed to be more efficient in terms of ridership, the original design called for the operation of 5,000 buses, a reduction from the number (7,700) of buses prior to the reform.

- New payment system: In order to make system integration effective and reduce on-the-street competition, a new payment mechanism was implemented under which transfer cost little or nothing. This mechanism was a contactless debit card (Tarjeta BIP), and all buses and the Metro were equipped with the devices capable of reading the information. BIP cards can be loaded with fare money using cash at special locations that include all Metro stations and other public spaces.[9]

The original plan was to start all at once in October 2005, a few months before the presidential election. However, with the deadline fast approaching and in view of technical

[8] These three key elements were part of the proposal made within the previous PTUS plan, which was implemented as policy during the administration of president Lagos in 2002 (Ureta, 2015)

[9] Prior to the implementation of Transantiago, Metro had already implemented a non-cash payment system, so it was not directly affected by the reform in this respect. However, since Metro was fully integrated into the transport system, after the reform passengers were allowed to transfer from buses to the Metro for a low cost.

difficulties such as the delay in the arrival of the new bus fleet and the installation of the new technological system supporting the new debit cards, the government decided to postpone the full implementation of the program. The government then specified that there would be a transition period, during which the new companies would go into operation using the existing bus routes and infrastructure. From a practical standpoint, this transition period would enable the government to avoid paying penalties related to delays that were stipulated in the contracts signed in 2004, and it would allow new companies to become familiar with the system by using the old routes. Five of the 15 new companies switched immediately to fixed-wage drivers' compensation (Johnson, Reiley, and Muñoz, 2015). In terms of system operation, the transition period meant no major changes for passengers except for the gradual introduction of the new buses. Services were not integrated with the Metro during this period and the same payment system (paying the driver in cash) remained. Another important modification during this transition period was the expansion of Metro's network from 45.3 km to 83.8 km during 2005-2006.

By contrast, in the final phase of the implementation of the reforms, the changes in the public transportation system were substantially more significant and abrupt. The core elements of the system (new routes and fare integration between all buses and the Metro) were all implemented on a single day –February 10, 2007– when the final stage of the Metro's network expansion was complete and operators had a significant portion of new buses available. The delay until the middle of February was intended to allow operators time to make some adjustments during the summer, which is a significantly less congested time of the year. The entire bus network began to operate along the new routes of the 15 service areas. In spite of many implementation problems, cash payments were completely eliminated from the system on the implementation date, and the BIP card was the only payment mechanism that could be used. People were required to charge their cards in advance. Furthermore, by using these cards passengers were allowed to transfer from any bus to the Metro or to another bus at no or low cost.

Given the main events associated with the implementation of Transantiago, I distinguish three main periods of analysis. The pre-reform period covers the first day for which crime data is available (January 1, 2005) until the launch of the so-called transition period of Transantiago (October 2005). The transition period is characterized by the large expansion of the Metro and the incorporation of new buses traveling along the old routes. The cash payment system was still in place during this period, but new firms were operating within the preexisting bus system and drivers started earning fixed salaries. During this period, new companies were assigned old routes according to the number of buses they had, but from the customer's point of view no significant changes were apparent in the system. Finally, the post-period begins abruptly on February 10, 2007 when the full integration between buses started and the cash payment system was replaced by the BIP card on buses. Figure 2 illustrates the timeline of events.

3 Analytical Framework: A Model for Criminal Activity

In this section, I lay out the features of a simple model of offender-victim interaction that will allow us to make explicit predictions associated with the level and nature of crime on buses during the various implementation phases of Transantiago. For simplicity, I consider two basic agents: potential offenders and bus drivers. Although passengers might have also suffered some portion of the crimes reported on buses, I do not expect any behavioral response associated with them during this period of analysis. The two agents in the model interact with each other, respectively, maximizing the gains or minimizing the losses of an eventual attack. I present the simplest version of the model, and I also include in the Appendix two additional specifications: i) a strategic interaction between agents with an endogenous model of the probability of attack, and ii) different levels of violence associated with the weapon used by the offender.

3.1 Bus Driver's Decision

Bus drivers decide either to oppose an attack with a high or low level of resistance: $r = \{H, L\}$. The level of resistance directly affects the chances of losing the cash in the fare-collection boxes when attacked. They take into account the expected losses (G_D), the costs of adopting a high-resistance strategy (c_i), which is idiosyncratic for each driver i, and the probability that the offender is successful in the attack as a function of the resistance (P_H, P_L). I assume that c_i has some empirical distribution $d\Omega(c)$. Also notice that $P_L > P_H$, which reflects that drivers have a strictly higher probability of avoiding any losses when exhibiting a high level of resistance during an attack.

Drivers decide based on the expected costs and benefits of each action. I consider drivers to be heterogeneous in terms of their costs of adopting a high-resistance strategy. Assuming a linear and additively separable utility function, driver's expected utility associated with each strategy (high or low level of resistance) can be written as:

$$U_i = \begin{cases} U_{H,i} = -P_H G_D - c_i, & \text{if } r = H \\ U_{L,i} = -P_L G_D, & \text{if } r = L \end{cases} \tag{1}$$

Drivers maximize their expected utility, $\max_r U_i$. Thus we can compute the likelihood that a randomly chosen driver i will exhibit high resistance (which I denote as H) as the proportion of drivers for whom the expected utility of high resistance exceeds the expected utility of low resistance:

$$H \equiv \Pr[U_H > U_L] = \Pr[-P_H G_D - c_i > -P_L G_D] = \Omega[(P_L - P_H) G_D] \tag{2}$$

Based on (2), the bus driver's decision rule as stated by equation (1) has a clear interpretation: the likelihood of adopting a high-resistance strategy depends directly on the expected losses (G_D), and the differential return of the high-resistance strategy $(P_L - P_H)$.

3.2 Offender's Decision

Potential offenders also consider a discrete choice: attacking or not attacking a bus driver. They attack when expected gains of attacking are larger than their opportunity cost (b_i). b_i represents potential gains from any other activity, including legal or other available illegal activities, and I consider that has some empirical distribution $d\Psi(c)$. I assume that potential offenders are heterogeneous in their opportunity costs. Expected gains are represented by G, which equals the amount of cash in the fare-collection boxes. Also, they consider the probability success (P_S), which depends on the level of resistance offered by the driver. Assuming that c_i is unobserved for a particular offender, but the offender knows its distribution $d\Omega(c)$ for a particular period of time, P_S can be written as: $P_S = HP_H + (1-H)P_L$, where H represents driver's likelihood of offering a high level of resistance. When attacking, offenders also have a generalized cost (S), which includes all perceived costs that are unrelated to sanction risk (formal and informal). Again, I assume a linear and additively separable utility function. Offenders' expected utility associated with each strategy are:

$$U_i = \begin{cases} U_{A,i} = P_S G - S, & \text{if } \textit{Attack} \\ U_{NA,i} = b_i, & \text{if } \textit{Don't attack} \end{cases} \tag{3}$$

Formally, if potential offenders maximize expected utility, their propensity to attack can be expressed as:

$$P_A \equiv \Pr[U_A > U_{NA}] = \Pr[b_i < P_S G - S] = \Psi[P_S G - S] \tag{4}$$

The expression in (4) has a direct interpretation: in a regime where drivers are more likely to resist we expect that gains from attacking a driver goes down as P_S decreases. Similarly, a variation in the expected reward (G) positively affects a potential offender's propensity to attack a bus driver.

3.3 Main Predictions

In this section I focus on different predictions regarding the level and nature of violence during the implementation of Transantiago. First, I discuss how the implementation of fixed salaries for bus drivers during the transition period, when fares were still paid exclusively in the form of cash, affected the level of crime observed. In a sense, this reform decoupled potential offenders' expected gains from drivers' losses. In other words, the transition period is represented by a shock that affected driver's propensity to protect the cash collected on each ride. I also discuss the effect on crime incidents of the implementation of the cashless debit card as the exclusive payment method starting in February 2007. In a way, this policy directly affected offenders' expected reward. Finally, in Section 6, I discuss how the introduction of a fixed-salary policy also affected the level of violence adopted by offenders, given the differential variation in driver's propensity to resist an attack.

3.3.1 Fixed-Salary Policy Leads to an Increase in Crime

The transition period decoupled gains from losses in the model. Offender's expected reward remained stable since there was no change in the payment system for riders. However, the implementation of fixed-salary policy drastically affected driver's propensity to resist an attack by reducing the loss associated with an attack (i.e., $G_D < G$). Formally, let d be the proportion of the loss born by the driver. In the pre-period $d = 1$. In the transition period, d fell below one (or may even have fallen to zero). Hence, the probability of exhibiting high resistance during these two periods can be written as

$$H \equiv H(t = pre) = \Omega[G(P_L - P_H)] \tag{5}$$

whereas in the transition period,

$$H' \equiv H(t = tra) = \Omega[(P_L - P_H)G_D] = \Omega[G(P_L - P_H) \times d] \tag{6}$$

Since $d < 1$, it is clear that $H > H'$, that is, driver's level of resistance unambiguously declined in the transition period. Similarly, we can see that $P_S \equiv P_{S,pre} < P_{S,transition} \equiv P_S'$, that is, offenders are more likely to success during the transition period.[10] Finally, given that offender's expected reward G remains invariant, we can see that robberies must increase in the transition period. The condition for an increase in crime rates $P_A < P_A'$ is given by:

$$P_A \equiv \Psi[P_S G - S] < \Psi[P_S' G - S] \equiv P_A' \tag{7}$$

which must be true since $P_S < P_S'$.

[10]A detailed proof is provided in the appendix section

3.3.2 Elimination of Cash Payment Reduces Criminal Incidents

In the post-reform period, a new payment method was introduced, eliminating the possibility of paying with cash on buses. This drastically reduces the expected reward from attacking bus drivers since they no longer collect cash. I model that by introducing a subscript in offender"s expected reward in the post-reform period. Formally, we have: $G_o < G$. It is clear that without a decrease in the resistance function, potential offenders' probability of attack will decrease. More generally, this depends on the extent to which the reduction in the expected reward offsets an increase in offender's probability of success. Considering again the pre-period as a benchmark, expected rewards can be substantially lower: $G_o << G$; but according to our model, due to the reduction in the expected losses driver's propensity to resist can be lower as well, which subsequently drives offender's probability of being successful to be larger: $P_S \equiv P_S(t = pre) > P_S(t = post) \equiv P_S''$. Thus, based on offender's propensity to attack, a general condition for a reduction in overall criminal activity, relative to the pre-reform period, is: $P_S'' G_o < P_S G$.

Overall, we may expect that the variation of the expected reward is much larger than the variation in offender's probability of being successful. Indeed, for the sake of simplicity we can assume that G_o is some value close to zero.[11] In that case, the implementation of the debit card payment system should lead to a drastic reduction in the number of cash-related robberies reported on buses.

4 Empirical Strategy

We aim to identify the effect on crime of the reforms initiated under Transantiago. We are interested in two main shocks that may have affected the overall level of criminal activity.

[11] The rationale for this is the following: In both periods, pre- and post-reform, drivers' discounted value in their propensity to resist remains the same, since they suffer every loss associated with an eventual attack ($d = 1$), but offender's reward G drastically decreases since cash payment was no longer available. More fundamentally, during the post-reform period drivers decide not only whether to resist an eventual attack but also offender's expected reward (amount of cash he/she decides to carry when driving). Since an eventual attack is costly, they strategically set out to carry an amount G_o as low as possible so as to eliminate incentive to offend. In that sense, there is no reason to believe that during the post-reform period rational offenders are still inclined to attack bus drivers as opposed to engaging in any other criminal or noncriminal activity (opportunity cost B).

First, I focus on the transition period, where new operators take over old routes and buses, and where bus driver compensation shifts from a proportion of revenue to a fixed salary. I then analyze the effect of converting the mechanism of fare payments on the bus from cash to electronic debit cards.

I propose three different but complementary strategies to estimate the effects associated with these particular periods and their surrounding circumstances: interrupted time series, difference-in-differences, and triple differences estimates. Since we have two different periods of interest (transition and post-reform), I use the pre-reform period as the reference category. Each of the identification strategies I propose rests on alternative identifying assumptions. While each individually can be limited, I believe they collectively complement one another and that in conjunction point to a causal effect of the reforms on crime rates. In this section, I first describe the data used in the study, and then how each identification strategies proposed complement to each other under this particular setting. In Section 5, I present the basic estimates associated with each alternative approach.

4.1 Data Description

I combine information about the timing of Transantiago with administrative data on all crimes reported to police between 2005 and 2010. Each record contains information about the time and location where the crime was perpetrated. Importantly for our research strategy, we can identify two main features of each crime: the place-category where the crime occurred and what was stolen, if anything (cash, noncash etc.).

The analysis focuses primarily on Santiago, Chile, a city with a population of approximately 6 million during this period. Importantly, data are collected and managed by the Chilean national police (*Carabineros de Chile*), which is a very centralized organization. Thus, we can be confident that the data are comparable across police departments over time.

I collapse the data to the weekly level.[12] Using all crimes reported during the three main periods of our analysis, I create a panel of different crime incidents reported in

[12]See Domınguez and Asahi (2019) for an analysis of variations in crime patterns associated with each day of the week.

specific places over 314 weeks. Table 1 compares the weekly average level for robberies reported on buses and street and public spaces. Robberies on buses represent a considerable portion, especially when we consider the high rate of incidents reported in Chile. Chile ranked 3rd (robbery rate = 600) among 56 countries, with an overall rate six times that of the United States ($approx$100 robberies per 100,000 people in 2014.[13] The robbery rate on buses during the pre-reform period equals the overall robbery rate (20 robberies per 100,000 people) of countries such as Hungary and Norway. Table 1 also shows how robberies on buses changed over time, with a large increase during the transition period and a considerable decrease in the post-policy period.

4.2 Strategy 1: Interrupted Time Series of Cash-Related Incidents on Buses

Figure 3 shows the evolution of cash-related robbery incidents reported on buses. It is clear from the time series that the pattern of Table 1 is more pronounced for this subgroup of crimes. During the transition period (October 2005 to February 2007) cash-related incidents increased substantially, which coincides with the period when drivers started to be paid fixed salaries, and the fare payment mechanism was still cash based. By contrast, right after the launch of Transantiago (February 2007), cash-related incidents dropped dramatically, and they remained stable at a very low level for the following three years. I run the following regression:

$$Crime_t = \alpha + \beta_1 Transition_t + \beta_2 Post_t + \omega_{m(t)} + \epsilon_t \quad (8)$$

$Crime_t$ represents the number of crime incidents reported on buses in week t. Importantly, all crime categories are computed by dividing the actual number of crimes during a week by the average weekly crimes reported in the pre-reform period for each specific crime category.[14] This denominator allows us to interpret regression coefficients

[13] UN Office on Drugs and Crime, 2014.

[14] The exact population at risk on buses is very difficult to measure; doing so should consider not only the daily rate of passengers but also the number who were riding a specific bus at a given moment. Unfortunately, temporally granular data on ridership are not available. Some empirical papers on crime have confronted a similar problem. Scholars typically used log-crime when looking at a similar population over time. One solution is offered by (Jacob, Lefgren, and Moretti, 2007, p.17), who worked with crime using overlapping jurisdictions. They suggest as a measure of criminal activity "the number of crimes committed during the

in percentage terms.

$Transition_t$ and $Post_t$ are indicator variables for whether the week t corresponds to the transition period (between October 2005 and February 2010) or the post-reform period (after February 2007). To analyze robustness of the coefficients, I also include in some specifications $Crime_{PS(t)}$, which is the number of incidents reported in the same category of the dependent variable (whether the good involved in the crime was cash or not) on streets and in public spaces in week t. The interpretation of the results when including $Crime_{PS(t)}$ should be undertaken with caution, since $Crime_{PS(t)}$ itself can be seen as an outcome (Angrist and Pischke, 2008) rather than properly controlling for other factors affecting criminal activity. Finally, $\omega_{m(t)}$ is a month fixed variable, which accounts for seasonal variation.

4.3 Strategy 2: Difference-in-Differences within Buses

A reasonable concern regarding strategy 1 is the ability to rely on a counterfactual scenario defined by the pre-policy period. In other words, we worry about the presence of additional contemporaneous changes that may have affected the evolution of cash-related robberies on buses. Without appropriately controlling for other potential factors affecting cash-related robberies in the public transportation sphere, our estimates would be confounded. Potential confounding factors can be changes implemented in the Metro system as well as the bus fleet, or any other change that affected the supply of criminal activity that were not present in the pre-policy period. In particular, the transition period coincided with a large expansion of the Metro system, whereas the post-policy period saw fare integration between the Metro and buses as well as an overall bus fleet reduction. Similarly, during the transition period bus companies were gradually incorporating a new bus fleet, which could potentially have affected the likelihood of incidents on buses.

In order to isolate the effect of the program from potential confounding factors, I implement a difference-in-differences (DD) approach incorporating noncash robbery incidents in the regression. If we assume that noncash robbery incidents (for example, robbery of cell phones or other consumer electronics) follow a similar pattern to that

week divided by the average weekly incidence in the jurisdiction during the sample period."

of cash-robbery incidents, and that this pattern was not altered during that period for any other reason than the reform of the driver's salary and the payment system, we can identify the effects of this reform. Figure 4 shows the evolution of both time series. We can observe that, during the pre-reform period, both curves show a similar pattern that motivates the use of noncash robberies as a counterfactual for how the trajectory of cash-related incidents would have evolved in the absence of the reform. Beginning with the transition period, these series move in opposite directions. Cash-related incidents increase dramatically, whereas noncash-related robberies remain stable. By contrast, during the post-reform period cash-related incidents drop sharply and the gap between the two curves remains remarkably stable during this entire three-year period. Notably, noncash robberies are stable throughout the three-year period, strongly suggesting that the reforms in particular impact the supply of cash-related opportunities, either through the weakening of the sentinel role played by the bus drivers or the elimination of the cash boxes. Hence, I propose the following difference-in-differences regression to estimate those coefficients:

$$\begin{aligned} Crime_{it} &= \alpha + \beta_1 Tra_t + \beta_2 Post_t + \beta_3 Cash_i + \beta_4 Cash_i \times Tra_t \\ &\quad + \beta_5 Cash_i \times Post_t + \omega_{m(t)} + \epsilon_{it} \end{aligned} \tag{9}$$

In this case, the dependent variable is the number of crimes reported in week t in the crime category i (cash- or noncash-related incident). Here I rely on the common trend assumption, which requires that in the absence of the policy both crime totals would follow similar trajectories. Later, I discuss the validity of this assumption and its ability to identify the effect attributed to the set of policies in place during each policy period.

4.4 Strategy 3: Triple Differences on Buses Relative to Public Spaces

Although the similar trajectory of cash- and noncash-related robberies during the pre-policy period, as well as the stability of noncash robberies afterwards, supports the validity of a difference-in-differences research design, I complement the results with a third strategy as a robustness check. As I have just discussed, valid estimates of the difference-in-differences coefficients require that both crime categories evolve similarly in expectation; this means that on average the proportional split between cash and noncash incidents reported on buses remained stable during the period of analysis. One potential concern might be the confounding presence of a more general trend affecting the proportion of incidents in each crime category compared in Figure 4. In particular, if any of the periods of analysis coincides with a trend that affected the proportion of cash- and noncash-related incidents in a broad sense, our common trend assumption will be violated. However, we can relax the common trend assumption and still recover the parameter of interest by adopting a triple differences approach.

To motivate the triple difference approach, I rely on Figure 5, which shows the evolution of robbery incidents (cash and noncash) reported in public spaces and on streets for our period of analysis. As in the case of buses, it shows a seasonal pattern; the period between July and October has the highest incidence level, which is consistent with how the level of regular activity rises and falls in a city like Santiago. Importantly, during the first three years, and despite the increase in noncash-related robberies, cash-related incidents are stable, around 150 incidents per week, eventually decreasing to 110 per week in the last year.[15] The proportional decline in cash-related incidents on streets and in public spaces suggests the presence of a large trend that may also affect our estimation within buses, when comparing cash- and noncash-related robberies.

To the extent that the observed differences in the proportion of cash- and noncash-related incidents affected incidents in public spaces and on buses alike, we can control for those differences, and finally identify the causal parameter of the relationship. I propose a triple differences approach incorporating robbery incidents reported on streets and in public spaces in Santiago. This estimation does not require that both crime categories

[15] In addition, the comparison of figures 4 and 5 provides a sense of the frequency of incidents on buses relative to streets and public spaces. During the pre-reform period, the proportion of cash-robbery incidents on buses (Figure 4) represents a considerable portion of the total incidents, and it is equivalent to 10 percent of the incidents reported on streets and in public spaces in the same crime category. Similarly, Figure 5 shows a substantially lower level of noncash-related incidents on buses relative to those in public spaces. In that sense, among the total robberies reported on buses, cash-related incidents represent a significantly higher proportion, around 50 percent of the total, relative to the proportion of cash-related incidents in robberies reported on streets and in public spaces, which is 25 percent

evolve in a similar way, but that any secular trend in the proportional split of robberies between cash and noncash incidents be similar for robberies on buses and robberies in public spaces.

Specifically, I estimate a regression of the following form:

$$\begin{aligned}
Crime_{ijt} = \alpha &+ \beta_1 Tra_t + \beta_2 Post_t + \beta_3 Cash_i + \beta_4 Cash_i \times Tra_t \\
&+ \beta_5 Cash_i \times Post_t + \beta_6 Bus_j + \beta_7 Bus_j \times Tra_t \\
&+ \beta_8 Bus_j \times Post_t + \beta_9 Bus_j \times Cash_i + \beta_{10} Tra_t \times Cash_i \times Bus_j \\
&+ \beta_{11} Post_t \times Cash_i \times Bus_j + \omega_{m(t)} + \epsilon_{ijt}
\end{aligned} \tag{10}$$

In this case, i refers to the type of crime (cash or noncash), j refers to the place (bus or public spaces), and t the period associated with each observation. From this estimation, β_{10} and β_{11} represent the parameters of interest associated with the effects of modifying driver's incentives and removing cash as the payment system, respectively. Again, I normalized all crime categories relative to the pre-policy period level.

5 Empirical Estimates

In this section, I present a set of estimates associated with the effect on overall crime activity during the implementation of Transantiago. I find consistent results from the various identification strategies outlined above, which I interpret as informative of the robustness of each of the research designs proposed. Moreover, those estimates are also consistent under different specifications, such as count models (Poisson) and OLS-regression using log-crime as the dependent variable. The last group of estimates are available in Appendix Tables 8-12.

5.1 Interrupted Time Series Estimates

Table 2 shows the basic coefficients using interrupted time series regressions. The dependent variable is defined as the weekly number of reported incidents divided by average number of weekly incidents during the pre-reform period. Thus, each coefficient can be read as the percentage change in crime for each period, relative to the level during the pre-policy period in the same crime category. In the first two columns for the noncash robbery regressions, coefficients are around 10% and 5% higher, relative to the pre-reform period, but neither of those differences are significant. For cash robberies, however, there are large and important changes. Relative to the pre-policy period, the transition period had 150% more incidents reported on buses, and this coefficient remains robust to the inclusion of incidents reported in public space as control. On the other hand, the post-policy period coefficient is -0.6, which means that incidents in that crime category where 60% lower than in the pre-reform period. This coefficient is robust to the inclusion of crime in public spaces as control, which suggests that potential spillovers from buses to public spaces does not affect the magnitude of the estimates. In addition to reporting robust standard errors, by including several Newey-West estimates I show that results are also robust to the number of lags.

5.2 Difference-in-Differences and Triple Differences Estimates

Although the magnitude of the previous estimates is substantially large, one might be worried about the ability to control for other contemporaneous changes that affect the evolution of cash-related robberies over time. As I have previously discussed, the variation relative to the evolution of noncash-related robberies can potentially define a counterfactual trajectory that allows us to evaluate the effect of the policies in place. Although the validity of the identifying assumption of each approach is untestable, an advantage of the DD research design is the ability to evaluate the common trend assumption by comparing the evolution of both types of crimes during the pre-policy period. Figure 4 shows that before Transantiago implemented any of the policies, both cash- and noncash-related robberies on buses evolved in a similar way. A triple difference design can relax the DD even further, capturing any systematic difference between cash- and noncash-bus robberies, relative to similar variations observed on streets and in public spaces.

Table 3 summarizes the coefficients I obtained from double and triple differences regressions. Again, coefficients are very large for the transition period and imply an increase around 120% and 140% in reported incidents, relative to the pre-reform levels. Similarly, coefficients for the post-reform period are significant, but results in columns 1 and 2 also suggest that the coefficient for post-reform period is sensitive to the length of the period considered. Overall, coefficients from Tables 2 and 3 show that results are consistent across all specifications.

One important consideration regarding the validity of each approach is the degree to which different types of crimes, rather than independent, are complementary or substitutes. Certainly, the presence of spillovers would bias our estimates. If substitutes, both cash and noncash crimes would move together, whereas the opposite is true for complementary crimes, where variation in the incidence of one is compensated by an opposite change in the incidence of the other. No spillover across different types of crimes is a fundamental assumption of our research design, and I will not be able to rule out that possibility with certainty. However, we can discuss the extent to which our coefficients could be biased in this regard.

If cash-related and noncash-related crimes are substitutes,[16] during the transition period we may expect that a portion of the increase in the former comes from a reduction in the latter. removing the incentives to protect the fare collection boxes on buses would have made cash much more attractive to steal relative to other potential objects. Thus, analyzing the variation in cash-related robberies using time series analysis would overestimate the total effect in crime. In the case of the post-policy coefficient, we can reach a similar conclusion where part of the reduction in cash-related crimes would occur in tandem with an increase in noncash robberies that in the absence of the reform would have not taken place. Again, time-series coefficients would overestimate (in absolute value) the total reduction in crime. In a similar way, under the substitution hypothesis, one might expect that DD coefficients would exacerbate the variation detected by using interrupted time series. Importantly, depending on the degree of substitution one can even imagine a scenario where time-series coefficients imply a crime reduction, though total crime could

[16]A similar analysis can be carried out if the types of crimes are complementary, although the expected results should go in the opposite direction

actually increase due to a larger variation in noncash robberies.

Based on the magnitude and consistency of the coefficients, as well as the characteristics of the reforms implemented under Transantiago, I argue that any potential spillovers would account for just a small portion of the variation captured by the estimates shown in tables 2 and 3. Table 2, as well as Appendix Tables 8, 11, and 12, provide extensive evidence that noncash-related crimes did not change during either the transition or the post-policy period. We observe a 10-15% increase that is barely significant in only a few specifications, and far from the 150% increase we observe in cash-related robberies during the transition period. Consistently, evidence of similar spillovers can be found when comparing DD and time-series transition estimates, since the former are larger than the latter –suggesting that the types of crime are complements. However, the fact that during the post-policy period DD coefficients are slightly larger, in absolute value, could indicate that the types of crime are more probably substitutes.

Another potential source of spillover bias has to do with the degree to which crimes on buses and in streets and public spaces relate to each other. I find little evidence in that regard as well. In Table 2 I include crimes that took place in streets and public spaces as a control variable, and all the estimates are remarkably robust to the inclusion of this covariate. On the other hand, if spillovers between crimes on buses and in public spaces are important, we would expect DD and DDD estimates to differ substantially. Given the different levels in terms of criminal activity across spaces, the analysis here must necessarily be more limited. We can observe that coefficients in Table 3 are fairly robust across specifications, and although I detect some differences for each period, I again cannot find consistent evidence of a specific trend in spatial spillover across periods. Differences between DD and DDD estimates would indicate some degree of substitution during the transition period, whereas post-policy estimates would suggest that criminal activities across public space and buses are complementary. In a way, the lack of clear evidence for one type of spillover across time and space seems to support the idea that they cannot explain the large variation we find for each relevant period.[17]

[17] It is plausible to think that under this particular setting both cash- and noncash-related crimes describe different situations: noncash robberies are likely to take place between bus passengers, while most of the cash-related robberies seem to be perpetrated against bus drivers. This is probably related with the prominent

5.3 Robustness

In order to further assess the validity of the research design, I run several model specifications and discuss potential threats to identification. First, I run an event-study model that provides a more transparent description of the temporal evolution of the estimates reported in Table 3. In essence, I modify equation (9) by interacting the cash-category variable with month-specific dummy variables instead of a single indicator for the transition and post-reform periods.

$$Crime_{it} = \alpha + \beta Cash_i + \sum_{i}^{T} \gamma_i 1[i = t] + \sum_{i}^{T} \delta_i 1[i = t] \times Cash_i + \omega_{m(t)} + \epsilon_{it} \tag{11}$$

The coefficient of interest from equation (11) is the value of δ estimates, which are displayed in Figure 6. As is usual in event studies, I normalize to drop the coefficient for the year prior to the first policy change (transition period).

The results displayed in Figure 6 confirm the findings of Table 3: the transition period led to a large increase in cash-related incidents that disappeared almost entirely during the post-reform period. In the Appendix are histograms I plotted of all coefficients for each relevant period using event studies at the monthly and weekly levels. In both cases the distribution of coefficients is clearly different from zero.

I also analyze robustness to the unit of analysis. I reproduce the main results using municipality-level panel data. Similar to the city-level models, I use the number of robbery incidents per week divided by the weekly average level during the pre-reform period as the dependent variable. Thus, the coefficients in Table 4 can be interpreted as percentage change and represent within-municipality estimates of the effect of the reforms introduced by Transantiago. Each panel reproduces the three main estimation methods used previously, and I include four specifications considering weighted and unweighted regressions, as well as weekly and period-level panel data. Given that municipalities differ in terms of pre-policy levels of criminal activity reported on buses, I analyze how robust the findings are to the inclusion of pre-reform period level of cash-related robbery

presence of cash on buses, which could also explain the large proportion of cash-related robberies I find on buses that is not observed in other spaces such as on streets and elsewhere.

weights.[18]

Overall, Table 4 shows that the results are robust to the unit of analysis. Relative to the city-level findings, the coefficients in Table 4 are remarkably similar. In addition, I observe the same pattern across specifications, where slightly larger transition estimates are found using interrupted time series, and larger (in absolute value) post-policy estimates are found using a difference-in-differences approach.

In terms of statistical inference, one might be worried that standard errors using weekly data can be biased due to serial correlation (Bertrand, Duflo, and Mullainathan, 2004). This can be especially problematic when using city-level data. The coefficients in Table 4 can offer a solution by clustering standard errors at the municipality level. In that sense, we notice that the standard errors in Table 4 are larger than the ones obtained using city-level data. In addition, by disaggregating the data at the municipality level, we can also correct for serial correlation by collapsing the data at the period level (Bertrand, Duflo, and Mullainathan, 2004). Columns 3 and 4 in Table 4 show results at the municipality-period level. As expected, standard errors are slightly larger but fairly stable across specifications, and even in the most conservative scenario, the coefficients remain highly significant.

I also analyze sensitivity to outliers at the municipality level, which can alert us to any unusual distribution of the results. Given that the coefficients in Table 4 represent percentage variation at the municipality level, one might be worried that they are sensitive to the exclusion of municipalities that experienced large variations, especially those with low baseline levels in terms of cash-related robberies during the pre-policy period. I follow the same specification of Table 4, and I test for outliers by running separate regressions at the municipality level but excluding one municipality at a time from the sample. Figures 15, 7, and 16 summarize those results for different estimation methods: interrupted time series, difference-in-differences, and triple differences.[19] In each figure municipalities excluded from the sample are sorted in the horizontal axis according to the level of cash-related robberies on buses during the pre-reform period. The coefficients

[18] Results are similar when using alternative municipality weights, such as average number of robberies on buses, considering both cash- and noncash-related incidents

[19] Figures 15 and 16 can be found in the Appendix.

represent within-municipality percentage variation relative to the pre-reform period. I also plotted the pre-reform level of cash-related robberies of the excluded municipality in the secondary vertical axis. In all three specifications, estimates are remarkably robust to dropping a given municipality.

Finally, I discuss the extent to which results are driven by a particular hour of the day or day of the week. Heterogeneous responses along either of the two dimensions can be informative in terms of how the reform was actually implemented. This is particularly important for transition estimates, where a portion of the large increase could have been driven by drivers' strategic behavior. Since bus drivers are no longer fully responsible for protecting fare revenues, it is possible that they strategically report false incidents to the police and simulate being a victim of a robbery while keeping the collected revenues for themselves. Although this would reflect a moral hazard problem induced by the new salary policy, the connection to our model of interaction between potential victims and offenders would be different. In that sense, unless drivers as a group can replicate the original distribution of incidents, we should not expect responses to be concentrated at a particular moment of the day or on a specific day of the week (e.g., most profitable hours in terms of revenue available in the fare collection box). I investigate this possibility by running separate regressions at different moments of the day and on different days of the week.

Figure 8 shows our coefficients of interest using different estimation methods at the city level and restricting the sample for each day of the week. The dashed blue line connects pre-policy levels of cash-related robberies on buses for each day of the week. The left panel shows how transition coefficients differ by day of the week, while the right panel shows similar estimates for the post-policy period. In both panels we can observe that coefficients are fairly stable, with the sole exception of Saturdays, where transition estimates are somehow smaller. To some extent this is to be expected, given the relatively higher baseline level observed on Saturdays. In the Appendix, I include Figure 17, which reports similar results by comparing estimates across hours of the day. Again, results are stable across model specifications and different times of the day. Overall, figures 8 and 17 confirm the magnitude of the effects for each period, and provide little or no evidence to support the idea that the increase in crime during the transition period was caused by drivers' strategic behavior.

6 Victims' Resistance and the Threat of Lethal Force

In addition to the effect on overall criminal activity, I analyze the extent to which the offenders-victims model describes the propensity to use more lethal and thus more threatening weaponry in the commission of a robbery. In this section, I focus on an ancillary prediction of the model pertaining to the nature rather than the level of crime. This is an important dimension in criminal analysis and one concerning which the empirical evidence is still scarce. Recent developments in the cost of crime literature emphasize that cost-benefit calculations are highly sensitive to the impacts of policy on violent crime, especially crimes resulting in fatalities (Chalfin and McCrary, 2013; Domınguez and Raphael, 2015). In that sense, the eventual preference for a situation with less crime can be reversed in favor of a situation with more but less-violent crime activity.

I present an extension of the offender-victim interaction model including offender's weapon choice. What matters here is how relative returns to making the most lethal threats could have been altered by the change in driver incentives induced by different salary structures. I conclude this section by testing empirically the model prediction for the transition period, during which more crime, but crime of a less violent nature, occurred.

6.1 Main Prediction: Fixed-Salary Policy Leads to a Smaller Proportion of Firearm-Related Incidents

The idea here is to analyze the extent to which the transportation reform affected the level of violence of the incidents reported to the police. I discuss how the reform may have affected the likelihood of perpetrating a crime using a particular weapon, which ultimately depends on how the reform altered chances of being successful using that particular weapon. I focus on whether the transition period affected offender's incentives for using a particular weapon. For this analysis, I slightly modify the specifications for each agent, incorporating a sub-index in many parameters of the model. Please see the Appendix for specific details.

I also incorporate an additional random component m_i, which captures the moral aversion (cost) of using a more lethal weapon when attacking a driver. For simplification, I consider only two possible weapons: firearms and knives. In this case, bus drivers decide their level of resistance against an eventual attack based on the particular weapon used by the offender. The cost of exhibiting a high level of resistance represents their idiosyncratic disposition to resist an attack with a particular weapon.

To focus on how the new compensation incentives altered the potential lethality of a crime in my model, I focus specifically on what determined the probability that a firearm was used in the robbery. By assuming a certain distribution of m_i, we can easily compare P_F for each period:

$$P_F = \Pr[U_F > U_K] = \Pr[m_i < G \times (P_{SF}(G_d) - P_{SK}(G_d)) - S_F + S_K] \tag{12}$$

During the transition period, we know that G_D (driver's losses) was decoupled from G (offender's expected gains). Basically, the model predicts very plausible condition under which the transition period leads to a less violent incident in terms of the use of a more lethal weapon. In particular, I found that offender's likelihood of using a firearm declined. Formally, I show that $P_F(t = pre) > P_F(t = tra)$. This condition holds when:

$$P_{SK}(G_d) - P_{SK}(G) > P_{SF}(G_d) - P_{SF}(G) \tag{13}$$

(13) depends on how the chances of being successful (P_S) vary between the pre-period and the transition period. In the Appendix, I discuss the specific conditions required for this prediction. The basic intuition is that the benefit from using a firearm is greater when victims are more likely to exhibit a high level of resistance. With a decline in the incentive for drivers to resist (their pay no longer depends on the outcome of the robbery) offenders substitute towards less-lethal threats (e.g., knives).

6.2 Gun Robberies vs. the Use of Less-Lethal Weapons

Figure 9 shows the evolution of cash-related robberies on buses, differentiating the kind of weapon used in the attack. Interestingly, we can see that all weapon incidents increased during the transition period, but the proportion of firearm-related incidents decreased. This is precisely consistent with our theoretical prediction based on the smaller returns associated with the use of that particular weapon during that period.

In order to test empirically a significant variation in the proportion of gun-related incidents, I run the following regression:

$$Prop.Firearm_t = \alpha + \beta_1 Transition_t + \beta_2 Post_t + \omega_{m(t)} + \epsilon_t \tag{14}$$

Table 5 shows the results for regression (14). The transition period is associated with a significant 8 percent decline in the proportion of firearm incidents. This finding is consistent to other specifications.[20] Although this period experienced a large increase in criminal activity, most of the increase was driven by less-lethal incidents in terms of the weapon used. We can notice that some results for the post-reform period are also significant and similar in magnitude to the ones obtained for the transition period; however, this variation is sensitive to the length of the post-reform period. Indeed, when I exclude years 2009 and 2010 from the sample (columns three and four), post-reform coefficients are much smaller in magnitude and no longer significant. Table 5 confirms the model's prediction that the increase in criminal activity associated with the change in driver's incentives to resist also modified the level of violence drivers were exposed to during the transition period. As a robustness check, in Appendix Table 17 I present results from similar regressions using noncash-related incidents reported on buses for the same period, and I find no significant results in terms of the weapon used in the incident.

Finally, Table 6 compares the proportion of victims that report some injury conditioned on being attacked with a particular weapon over time. Here I focus on the proportion of victims injured within a particular crime category determined by the weapon used by the offender. If drivers are effectively opposing a lower level of resistance during the

[20] See Tables 15 and 16 in the Appendix

transition period, we may expect that the proportion who were injured when robbed declined.

Table 6 shows that across all weapon categories the proportion of victims reporting some injury declined, but the reduction is particularly large for knife-related incidents. Importantly, the fact that there is almost no variation in the firearm-crime category reinforces the model's prediction of heterogeneous weapon return variation imposed by the new policy regime. Table 18 in the Appendix provides a similar comparison in terms of noncash-crime category; a pattern comparable to those described above for knife-related and firearm-related incidents is not evident, however.

7 Conclusion

In this paper I describe criminal activity as the interaction between potential offenders, victims, and the environment. I show that the set of criminal opportunities available to offenders is shaped by the environment and what potential victims do. I discuss how offenders respond and adapt to those opportunities presenting a simple model that can be informative to understand the level and characteristics of criminal activity. I test the model's predictions empirically, exploiting the specific features of a sequential set of reforms implemented in the public transportation sector in Santiago, Chile.

There are two main empirical findings. First, during the period where drivers' salaries were strictly attached to fare revenues, we observe a relatively small proportion of cash-related robberies (50% of robberies on buses). In turn, robberies surge when drivers started to be paid fixed salaries, and this variation is entirely driven by cash-related incidents. The magnitude of this increase is substantial and reinforces the idea that private behavior is an important omitted variable in understanding victimization. If I impose some basic assumptions to make the reaction functions tractable,[21] we can see that the overall response in terms of the increase in crime during the transition period suggests that driver's resistance strategy can reduce offender's probability of success from 1 (under the low-resistance strategy) to 0.4 (under the high-resistance strategy). The

[21] See Online Appendix note B.4 for details.

attractiveness of fare-collection boxes for criminal purposes became much more apparent when incentives to protect them were removed.

I also find variation in another relevant dimension of criminal activity associated with this change in driver-salary policy. This finding suggests that although victims can do a lot to avoid being victimized, it may come at a high personal cost. I find that during the pre-reform period, when the crime was relatively low, drivers were exposed to a higher level of violence when they were robbed. This is a crucial consideration with welfare implications. Reducing crime rate is an important goal, but so is harm reduction (Cook, 2014). This additional dimension of welfare can be considered more explicitly when evaluating anticrime policies. It also suggests caution with regard to policies that seek to reduce crime based on increasing victims' propensity to resist, as such policies may also induce a substantial increase in the level of violence exhibited by offenders.

The second main finding is the abrupt decline in crime caused by the eradication of cash transactions. Although it is associated with a specific context –incidents on buses– it has implications for other crime settings. A decline in the use of cash in everyday life transactions has been suggested as an alternative explanation for the observed decline in crime in the United States in the last two decades. Although the effect I found is strictly local, its magnitude suggests a promising area of research. To put the magnitude in perspective, consider the following thought experiment. What variation in the probability of successfully resist an attack is associated with the observed change in crime between the pre-reform and post-reform period? What size increase in police presence on buses would be equivalent to the impact associated with using cash as the only payment mechanism? It would be a challenge to find a comparable scenario involving other public space settings, but considering common crime-police elasticity estimates found in the literature, an equivalent overall reduction in crime would be reached with a substantial increase in police presence (between 160% and 300% using the estimates of Chalfin and McCrary (2013) and Di Tella and Schargrodsky (2004), respectively).[22]

Transantiago was a very ambitious plan that modified the bus system in a radical way.

[22] Di Tella and Schargrodsky (2004) find a police-crime elasticity of -0.3 for vehicle theft, while the results of Chalfin and McCrary (2013) suggest a -0.56 estimate for robbery.

In this paper, I take advantages of its main features to learn about criminal activity rather than presenting an exhaustive evaluation of the program. Given the large scope of the reform, we can imagine many alternative channels that could affect the interpretation of our findings. To address that concern, I present a set of results that exploits the sequential implementation of the reforms but relies on different identification assumptions. I interpret both the magnitude and consistency of the results as robust evidence of how offenders respond to the set of opportunities available to them.

Finally, I would like to stress a final point about system regulation and some of its implications. Exact-change fare collection with on-board secure boxes as a crime-prevention tool has been the standard in the United States since the early 1970s. This kind of system was implemented following a public debate regarding security on buses and nowadays seems to be part of a basic standard in public transportation. What is striking is the fact that despite the availability of a simple and effective crime-prevention tool, open-fare collection boxes are still present in the public transportation sectors of many cities across the world. This begs the further research question regarding what prevents policy makers from adopting these basic safety measures. A tentative hypothesis has to do with a lack of regulation in the public transportation sector, a characterization that aptly describes the bus system in Santiago prior to the reform. If buses are simply competing in the streets for capturing the largest possible number of passengers per ride, it seems plausible to believe that both agents, bus owners and drivers, have strong incentives to keep open-fare collection boxes in place, even at the expense of a higher risk of violence and victimization. From a bus owner's perspective, this may encourage drivers to directly control fare evasion, a common problem in the public transportation sector. At the same time, the use of cash may allow drivers to increase their salaries by charging a lower fare to those passengers willing to ride without a ticket. Light regulation of the public transportation sector does little to incentivize the implementation of simple crime-prevention measures. In this case, the final product can be the persistent presence of a highly attractive criminal opportunity.

References

Angrist, Joshua D and Jörn-Steffen Pischke (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Ayres, Ian and Steven D Levitt (1998). "Measuring positive externalities from unobservable victim precaution: an empirical analysis of Lojack". In: *The Quarterly Journal of Economics* 113.1, pp. 43–77.

Becker, Gary S (1968). "Crime and punishment: An economic approach". In: *Journal of political economy* 76.2, pp. 169–217.

Beltrán, Pablo, Antonio Gschwender, and Carolina Palma (2013). "The impact of compliance measures on the operation of a bus system: the case of Transantiago". In: *Research in Transportation Economics* 39.1, pp. 79–89.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan (2004). "How much should we trust differences-in-differences estimates?" In: *The Quarterly journal of economics* 119.1, pp. 249–275.

Briones, Ignacio (2009). "Transantiago: Un problema de información". In: *Estudios Publicos* 16, pp. 37–91.

Buonanno, Paolo and Steven Raphael (2013). "Incarceration and incapacitation: Evidence from the 2006 Italian collective pardon". In: *The American Economic Review* 103.6, pp. 2437–2465.

Chaiken, Jan M, Michael W Lawless, and Keith A Stevenson (1974). *The impact of police activity on subway crime*. Tech. rep. RAND Corp, Santa Monica, California.

Chalfin, Aaron and Justin McCrary (2013). *The effect of police on crime: New evidence from US cities, 1960-2010*. Tech. rep. National Bureau of Economic Research.

Cheng, Cheng and Mark Hoekstra (2013). "Does strengthening self-defense law deter crime or escalate violence? Evidence from expansions to castle doctrine". In: *Journal of Human Resources* 48.3, pp. 821–854.

Clotfelter, Charles T (1977). "Public services, private substitutes, and the demand for protection against crime". In: *The American Economic Review* 67.5, pp. 867–877.

Cook, Philip J (1977). "Punishment and crime: a critique of current findings concerning the preventive effects of punishment". In: *Law and contemporary problems* 41.1, pp. 164–204.

— (1979). "The clearance rate as a measure of criminal justice system effectiveness". In: *Journal of Public Economics* 11.1, pp. 135–142.

— (1986). "The demand and supply of criminal opportunities". In: *Crime and justice* 7, pp. 1–27.

— (2014). "Robbery". In: *Encyclopedia of Criminology and Criminal Justice*, pp. 4502–4510.

Cook, Philip J and John MacDonald (2011). "Public safety through private action: an economic assessment of BIDS". In: *The Economic Journal* 121.552, pp. 445–462.

Cook, Philip J, Stephen Machin, et al. (2013). "Crime economics in its fifth decade". In: *Lessons from the Economics of Crime: What Reduces Offending?*, p. 1.

Di Tella, Rafael and Ernesto Schargrodsky (2004). "Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack". In: *The American Economic Review* 94.1, p. 115.

Dıaz, Guillermo, Andrés Gómez-Lobo, and Andrés Velasco (2004). *Micros en Santiago: de enemigo público a servicio público*. 357. Centro de Estudios Públicos.

Domınguez, Patricio and Kenzo Asahi (2019). *Crime Time: How Ambient Light Affects Crime*. Tech. rep. Inter-American Development Bank.

Domınguez, Patricio and Steven Raphael (2015). "The Role of the Cost-of-Crime Literature in Bridging the Gap Between Social Science Research and Policy Making". In: *Criminology & Public Policy* 14.4, pp. 589–632.

Draca, Mirko, Stephen Machin, and Robert Witt (2011). "Panic on the streets of london: Police, crime, and the july 2005 terror attacks". In: *The American Economic Review* 101.5, pp. 2157–2181.

Easteal, Patricia Weiser and Paul Richard Wilson (1991). "Preventing crime on transport: Rail, buses, taxis, planes". In:

Freeman, Richard B (1999). "The economics of crime". In: *Handbook of labor economics* 3, pp. 3529–3571.

Gómez-Lobo, Andrés (2007). "Transantiago: una reforma en panne". In: *TIPS, Trabajos de Investigación en Polıticas Públicas* 4, pp. 1–14.

Gonzalez-Navarro, Marco (2013). "Deterrence and geographical externalities in auto theft". In: *American Economic Journal: Applied Economics* 5.4, pp. 92–110.

Gray, Paul (1971). "Robbery and assault of bus drivers". In: *Operations Research* 19.2, pp. 257–269.

Jacob, Brian, Lars Lefgren, and Enrico Moretti (2007). "The dynamics of criminal behavior evidence from weather shocks". In: *Journal of Human resources* 42.3, pp. 489–527.

Johnson, Ryan M, David H Reiley, and Juan Carlos Muñoz (2015). ""The war for the fare": How driver compensation affects bus system performance". In: *Economic Inquiry* 53.3, pp. 1401–1419.

Levitt, Steven D (1996). "The effect of prison population size on crime rates: Evidence from prison overcrowding litigation". In: *The quarterly journal of economics* 111.2, pp. 319–351.

— (2002). "Using electoral cycles in police hiring to estimate the effects of police on crime: Reply". In: *The American Economic Review* 92.4, pp. 1244–1250.

— (2004). "Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not". In: *The Journal of Economic Perspectives* 18.1, pp. 163–190.

Mayhew, Pat, Ronald V Clarke, and David Elliott (1989). "Motorcycle theft, helmet legislation and displacement". In: *The Howard Journal of Crime and Justice* 28.1, pp. 1–8.

McClellan, Chandler and Erdal Tekin (2017). "Stand your ground laws, homicides, and injuries". In: *Journal of human resources* 52.3, pp. 621–653.

Muñoz, Juan Carlos and Antonio Gschwender (2008). "Transantiago: A tale of two cities". In: *Research in Transportation Economics* 22.1, pp. 45–53.

Muñoz, Juan Carlos, J de D Ortúzar, and Antonio Gschwender (2009). "Transantiago: the fall and rise of a radical public transport intervention". In: *Travel demand management and road user pricing: Success, failure and feasibility*, pp. 151–172.

Nagin, Daniel S, Robert M Solow, and Cynthia Lum (2015). "Deterrence, criminal opportunities, and police". In: *Criminology* 53.1, pp. 74–100.

O'Flaherty, Brendan (2015). *The Economics of Race in the United States*. Harvard University Press.

O'Flaherty, Brendan and Rajiv Sethi (2008). "Racial stereotypes and robbery". In: *Journal of Economic Behavior & Organization* 68.3-4, pp. 511–524.

— (2010). "Homicide in black and white". In: *Journal of Urban Economics* 68.3, pp. 215–230.

Olavarrıa Gambi, Mauricio (2013). "De la formulación a la implementación del Transantiago: Análisis del proceso polıtico de una polıtica pública". In: *Gestión y polıtica pública* 22.2, pp. 355–400.

Pearlstein, Adele and Martin Wachs (1982). "Crime in public transit systems: An environmental design perspective". In: *Transportation* 11.3, pp. 277–297.

Rogoff, Kenneth S (2016). *The curse of cash*. Princeton University Press.

Shavell, Steven (1991). "Individual precautions to prevent theft: private versus socially optimal behavior". In: *International Review of Law and Economics* 11.2, pp. 123–132.

Smith, Martha J and Ronald V Clarke (2000). "Crime and public transport". In: *Crime and Justice* 27, pp. 169–233.

Ureta, Sebastián (2015). *Assembling Policy: Transantiago, Human Devices, and the Dream of a World-class Society*. Mit Press.

Van den Haag, Ernest (1975). *Punishing criminals*.

Vollaard, Ben and Jan C Van Ours (2011). "Does Regulation of Built-in Security Reduce Crime? Evidence from a Natural Experiment". In: *The Economic Journal* 121.552, pp. 485–504.

Wright, Richard et al. (2014). *Less cash, less crime: Evidence from the electronic benefit transfer program*. Tech. rep. National Bureau of Economic Research.

Zimring, Franklin E (2006). *The great American crime decline*. Oxford University Press, USA.

A Appendix

Table 1: Robberies on Buses and Public Space-Streets by Period

	Buses				**Street and Public Spaces**			
	Noncash		Cash		Noncash		Cash	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Pre	12.40	(0.77)	11.38	(0.68)	346.88	(7.90)	139.76	(3.04)
Transition	14.65	(0.54)	28.18	(1.39)	403.57	(7.53)	141.13	(1.70)
Post	14.04	(0.35)	3.76	(0.16)	409.19	(4.79)	124.89	(1.80)

Notes: Values are weekly averages for each period. Cash- and noncash-related incidents are classified based on the good stolen reported by the victim.

Table 2: Interrupted Time Series Estimates: Robbery on Buses

	(1) Noncash	(2) Noncash	(3) Cash	(4) Cash
Transition	0.155*	0.108	1.521***	1.522***
	(0.060)	(0.070)	(0.120)	(0.120)
Post	0.0923	0.0459	-0.673***	-0.616***
	(0.060)	(0.060)	(0.060)	(0.060)
Robb_PS	No	Yes	No	Yes
Pre-reform Level of DV	12.40	12.40	11.38	11.38
N	314	314	314	314
R-sq	0.297	0.307	0.786	0.792

Notes: Coefficients using interrupted time-series on each crime category. $Robb_{PS}$ represents robberies in the same crime category in streets (cash- or noncash-related incidents). Crime rates are divided by the weekly average reported in the pre-period in the same crime category. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 3: Double and Triple Differences Estimates: Robbery

	(1) DD	(2) DD	(3) DDD	(4) DDD
Trans x Cash (x Bus)	1.295***	1.295***	1.449***	1.449***
	(0.130)	(0.130)	(0.150)	(0.140)
Post x Cash (x Bus)	-0.802***	-0.671***	-0.516***	-0.415***
	(0.080)	(0.080)	(0.090)	(0.090)
Pre-reform level of Cash-Incidents	11.38	11.38	11.38	11.38
N	628	416	1,256	832
R-sq	0.716	0.711	0.676	0.674

Notes: Coefficients from DD and DDD regressions including monthly fixed effects. First and third columns using full period (2005-2010), and a restricted sample in columns two and four (2005-2008; n2=52x2x4; n4=52x2x4x2). Crime rates are divided by the weekly average reported in the pre-period in the same crime category. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Figure 1: Driver' Space inside a Bus during Pre-reform and Transition Period

Notes: Open-fare collection box ("peceras") located at the right-hand side of the driver. They allowed drivers to collect cash and provide tickets and cash back to passengers accordingly. Source: http://mqltv.com/10-cosas-recordaras-viajaste-una-micro-amarilla/ extracted on 3-19-2017

Figure 2: Timeline of the Events: Pre-reform, Transition, and Post-reform Periods

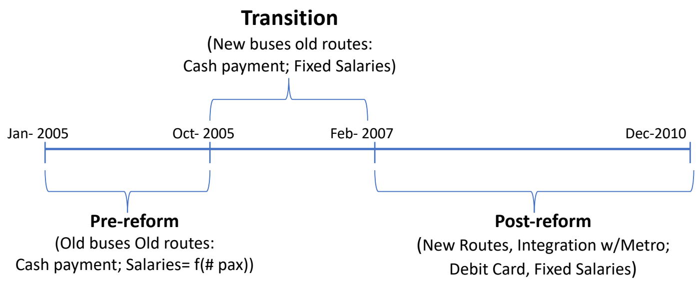


Table 4: Coefficients Using Municipality-Level Panel Data

Panel A: Interrupted Time Series				
Transition	1.695***	1.793***	1.632***	1.746***
	(0.295)	(0.347)	(0.352)	(0.418)
Post	-0.547***	-0.650***	-0.556***	-0.650***
	(0.082)	(0.042)	(0.091)	(0.061)
N	9,703	9,703	93	93
R-sq	0.096	0.177	0.695	0.736
Panel B: Difference-in-differences				
Trans x Cash	1.216**	1.534***	1.216**	1.534**
	(0.335)	(0.407)	(0.373)	(0.453)
Post x Cash	-0.981***	-0.931***	-0.981***	-0.931***
	(0.165)	(0.213)	(0.183)	(0.237)
N	18,780	18,780	180	180
R-sq	0.063	0.108	0.552	0.593
Panel C: Triple Differences				
Trans x Cash x Bus	1.273***	1.532***	1.273**	1.532**
	(0.330)	(0.398)	(0.350)	(0.422)
Post x Cash x Bus	-0.740***	-0.683**	-0.740***	-0.683**
	(0.173)	(0.203)	(0.183)	(0.216)
N	38,186	38,186	366	366
R-sq	0.055	0.097	0.507	0.56
Weights	N	Y	N	Y
Frequency	Weekly	Weekly	Period	Period

Notes: Coefficients estimated using weekly or period municipality-level data considering 31 municipalities of Santiago urban metropolitan area. All regressions include municipality fixed effects. Weights are calculated based on the number of cash-related incidents during the pre-reform. On average, during the pre-reform period, municipalities have 0.32 (cash-related) and 0.36 (noncash-related) weekly robbery incidents. Three municipalities with unusual levels of noncash-related robberies on buses during the pre-reform period were excluded from the sample, but weighted results are robust to the inclusion of these three municipalities. Robust standard errors clustered at the municipality level in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 5: Time Series Estimates: Proportion of Firearm Incidents, Cash Robbery on Buses

	(1)	(2)	(3)	(4)
Transition	-0.0877**	-0.0903**	-0.0877**	-0.0781*
	(0.030)	(0.033)	(0.031)	(0.035)
Post-Reform	-0.0903*	-0.0980**	-0.0332	-0.0318
	(0.035)	(0.033)	(0.039)	(0.037)
Month FE	N	Y	N	Y
YEAR<=2008	N	N	Y	Y
Pre-reform Mean of DV	0.417	0.417	0.417	0.417
N	72	72	48	48
R-sq	0.048	0.27	0.08	0.384

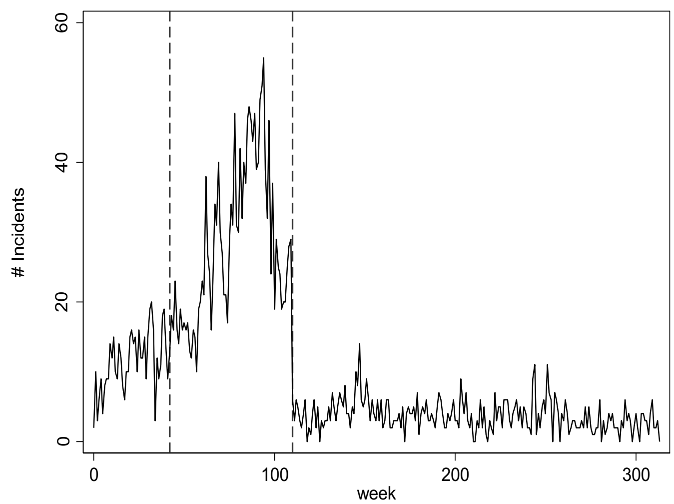
Notes: Coefficients using interrupted time-series. The dependent variable is the monthly amount of firearm cash-related incidents divided by the number of cash-related incidents reported on buses. Robust standard errors in parentheses.* p<0.05, ** p<0.01, *** p<0.001

Table 6: Proportion of Victims with Some Injury by Weapon Used: Cash-Related Incidents

Period	Pre		Transition		Post	
Weapon	Prop.S.I	# [Inc/M]	Prop.S.I	# [Inc/M]	Prop.S.I	# [Inc/M]
No Weapon	0.333	0.3	0.150	1.3	0.286	0.1
Firearm	0.083	23.0	0.073	44.9	0.108	6.9
Knife	0.114	25.4	0.071	69.3	0.154	8.4
Stick	0.300	1.3	0.235	3.4	0.321	0.6
Threat	0.333	2.5	0.290	4.6	0.398	2.4
Other	0.333	1.2	0.074	3.6	0.207	0.6
Total [Inc/Month]	53		127		19	

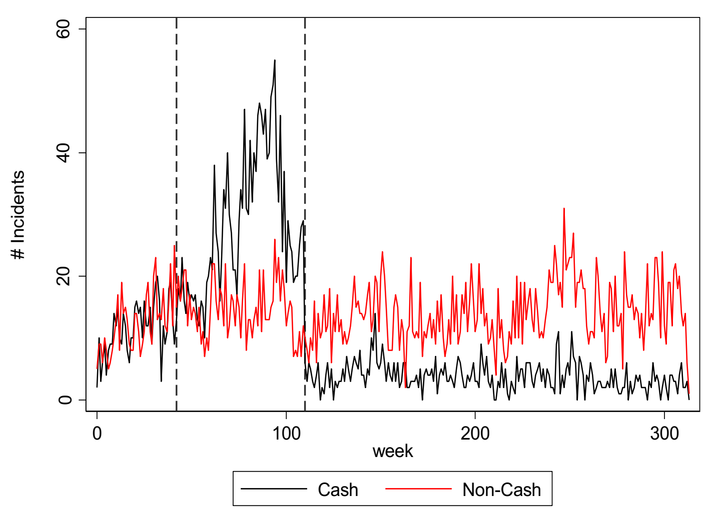
Notes: Prop.S.I is the proportion of victims that report some injury in each period. Inc/M number of incidents per month reported in each weapon-category for each period.

Figure 3: Cash-related Robbery Incidents on Buses: 2005-2010



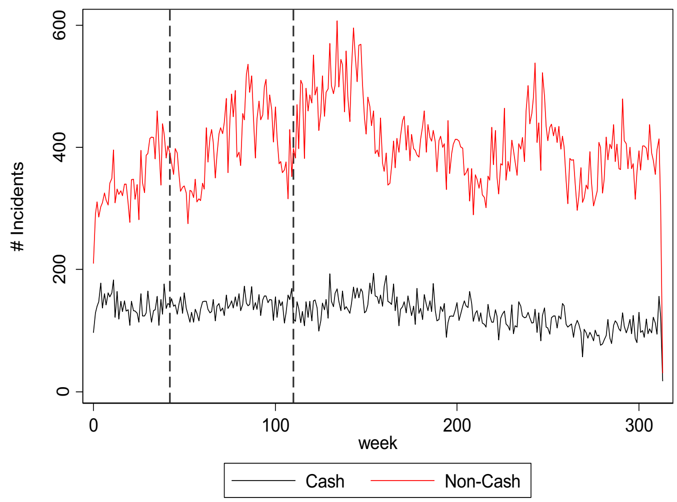
Notes: Lines connect weekly incidents. Vertical dashed lines show the beginning of the transition (October 2005) and the post-reform (February 2007) periods.

Figure 4: Robbery Incidents on Buses: 2005-2010



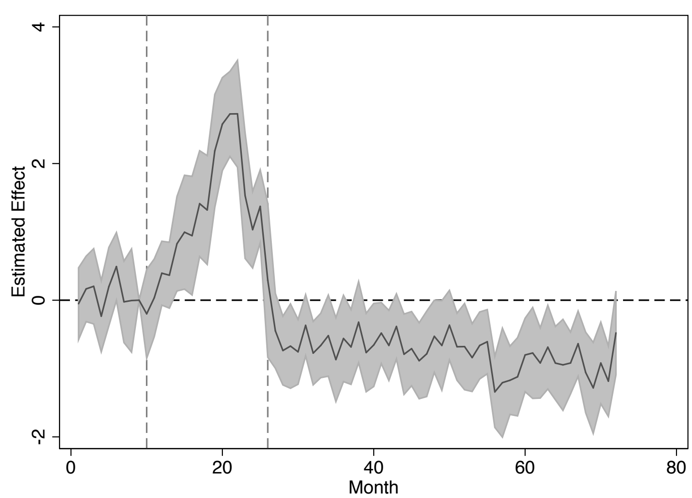
Notes: Lines connect weekly incidents. Black line connects weekly cash-related robberies while red line represents the evolution of noncash-related robberies reported on buses. Vertical dashed lines show the beginning of the transition (October 2005) and the post-reform (February 2007) periods.

Figure 5: Robbery Incidents on Streets and in Public Spaces: 2005-2010



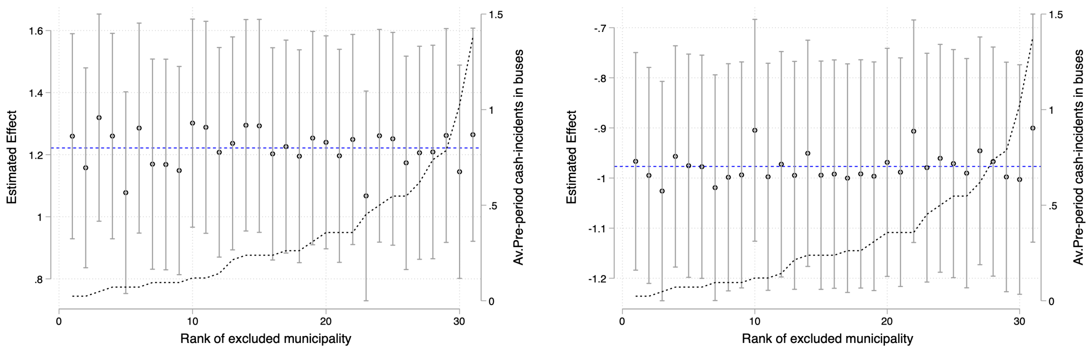
Notes: Lines connect weekly incidents. Black line connects weekly cash-related robberies while red line represents the evolution of noncash-related robberies reported in public spaces. Vertical dashed lines show the beginning of the transition (October 2005) and the post-reform (February 2007) periods.

Figure 6: Event-Study: Cash-Category Interacted with Month-Specific Indicators: 2005-2010



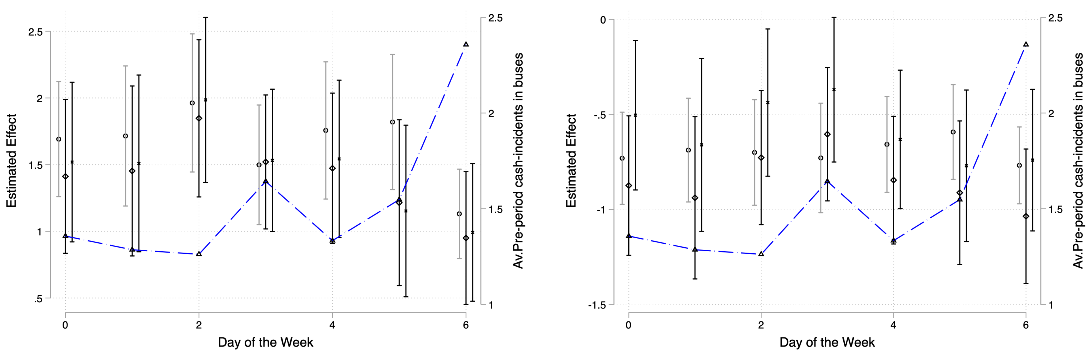
Notes: Lines represent the evolution of the interacted coefficients δ of equation (11) which represent the monthly effect on cash-related robberies reported on buses. Vertical dashed lines show the beginning of the transition (October 2005) and the post-reform (February 2007) periods.

Figure 7: Robustness of Estimated Treatment Effect to Dropping Municipalities: Difference-in-Differences



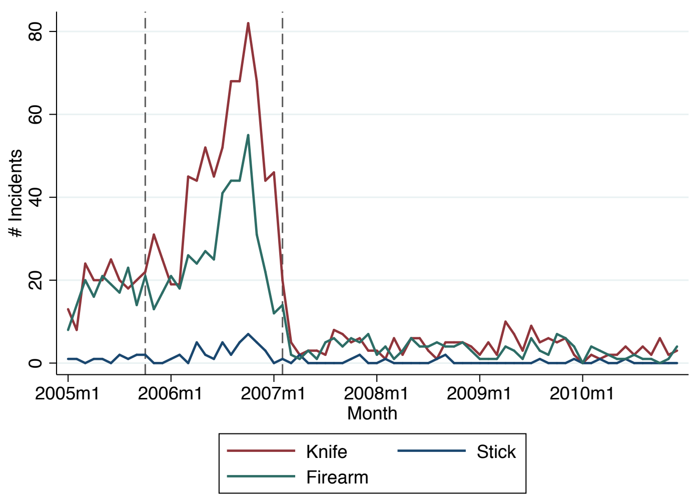
Notes: Figure shows difference-in-differences coefficients of separate unweighted regressions using municipality-level panel data but excluding one municipality at a time. Left-side figure shows estimates for the transition period while post-policy period estimates are plotted on the right side. All regressions include municipality by month fixed effects and standard errors are clustered at the municipality level. 95% confidence intervals are included. Municipalities excluded from the sample are indicated in the horizontal axis which are ranked by the level of incidents during the pre-policy period. Black dashed blue line connects average weekly level of cash-related robberies on buses during the pre-policy period, and references values are indicated in the secondary right-side vertical axis.

Figure 8: Robustness of Estimated Treatment Effect to Day of the Week



Notes: Figure shows coefficients estimated by running separate regressions for each day of the week. 95% confidence intervals are included for each estimate. Left side figure shows estimates for the transition period while post-policy period estimates are plotted at the right side. Coefficients estimated using different approaches: interrupted time series (circle), difference-in-differences (diamond), and triple differences (x). Dashed blue line connects weekly average level of cash-related robberies on buses during the pre-policy period, and references values are indicated in the secondary right-side vertical axis. Days of the week are sorted from Sunday (0) to Saturday (6).

Figure 9: Monthly Evolution Cash-related Robberies on Buses by Weapon Used: 2005-2010



Notes: Lines connect monthly evolution of cash-related robberies by weapon used reported on buses. Vertical dashed lines show the beginning of the transition (October 2005) and post-reform (February 2007) periods.

B Online Appendix

Table 7: Transportation Mode Evolution in Santiago, Chile

EOD	2001	2006	2012
Car	23.70%	20.81%	25.12%
Bus	25.92%	24.25%	12.80%
Bus-Metro	1.11%	1.17%	6.21%
Metro	2.27%	3.61%	5.42%
Car-Metro	0.18%	0.20%	0.78%
Taxi-Metro	0.59%	0.96%	1.60%
Taxi	3.72%	3.72%	4.47%
Walking	36.71%	36.81%	33.65%
Bicycle	1.87%	2.95%	3.95%
Other	3.94%	5.52%	6.00%
Metro Network (km)	39.7	66.4	102
Total Trips (MM)	16.28	17.33	18.46

Source: Adapted from Encuesta Origen-Destino, Subsecretaria de Transporte, Chile.

Table 8: Newey-West Regression Estimates: Robbery on Buses, Noncash Incidents

	1	2	3	4	5	6	7	8	9	10
Transition	0.155*	0.155*	0.155*	0.155*	0.155***	0.108	0.108	0.108	0.108	0.108**
	(0.065)	(0.068)	(0.061)	(0.062)	(0.043)	(0.069)	(0.072)	(0.067)	(0.068)	(0.041)
Post	0.0923	0.0923	0.0923	0.0923	0.0923	0.0459	0.0459	0.0459	0.0459	0.0459
	(0.056)	(0.057)	(0.053)	(0.061)	(0.064)	(0.062)	(0.062)	(0.054)	(0.061)	(0.060)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robb_PS	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
# Lags	1	4	12	26	52	1	4	12	26	52
N	314	314	314	314	314	314	314	314	314	314

Notes: Newey-West Coefficients are calculated using interrupted time-series on each crime category. $Robb_{PS}$ represents robberies in the same crime category (cash- or noncash-related incidents). All crime rates are computed by dividing the actual number of crimes during a week by the average weekly crimes reported in the pre-period in the same crime category. Robust standard errors are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 9: Newey-West Regression Estimates: Robbery on Buses, Cash Incidents

	1	2	3	4	5
Transition	1.521***	1.521***	1.521***	1.521***	1.521***
	(0.148)	(0.200)	(0.277)	(0.319)	(0.285)
Post	-0.673***	-0.673***	-0.673***	-0.673***	-0.673***
	(0.062)	(0.063)	(0.068)	(0.064)	(0.046)
Month FE	Yes	Yes	Yes	Yes	Yes
Robb_PS	No	No	No	No	No
# Lags	1	4	12	26	52
N	314	314	314	314	314

Notes: Newey-West Coefficients are calculated using interrupted time-series on each crime category. $Robb_{PS}$ represents robberies in the same crime category (cash- or noncash-related incidents). All crime rates are computed by dividing the actual number of crimes during a week by the average weekly crimes reported in the pre-period in the same crime category. Robust standard errors are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 10: Newey-West Regression Estimates: Robbery on Buses, Cash Incidents

	6	7	8	9	10
Transition	1.522***	1.522***	1.522***	1.522***	1.522***
	(0.146)	(0.196)	(0.272)	(0.313)	(0.280)
Post	-0.616***	-0.616***	-0.616***	-0.616***	-0.616***
	(0.065)	(0.066)	(0.074)	(0.066)	(0.045)
Month FE	Yes	Yes	Yes	Yes	Yes
Robb_PS	Yes	Yes	Yes	Yes	Yes
# Lags	1	4	12	26	52
N	314	314	314	314	314

Notes: Newey-West Coefficients are calculated using interrupted time-series on each crime category. $Robb_{PS}$ represents robberies in the same crime category (cash- or noncash-related incidents). All crime rates are computed by dividing the actual number of crimes during a week by the average weekly crimes reported in the pre-period in the same crime category. Robust standard errors are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001

B.1 Model 1. Potential Offender and Victim's Interaction

B.1.1 Fixed Salary Policy Leads to an Increase in Crime

Proof of declining in the offender's probability of success:

$$
\begin{aligned}
P_S \equiv P_S(t = pre) < P_S(t = tra) \equiv P_S' \\
H(G)P_H + (1 - H(G))P_L < H(G_d)P_H + (1 - H(G_d))P_L \\
H(G_d)(P_L - P_H) < H(G)(P_L - P_H) \\
H(G \times d) < H(G)
\end{aligned}
$$

which is true for any $d < 1$.

B.1.2 Elimination of Cash Payment System Reduces Criminal Incidents

Condition for a decrease in offenses in the post-reform period. We can simply compare variation in the probability of attack between pre-reform and post-reform periods.

$$
\begin{aligned}
Pa(t = pre) \equiv P(b_i < P_S G - S) > P(b_i < P_S'' G_o - S) \equiv P_a(t = post) \\
P_S G - S > P_S'' G_o - S \\
P_S G > P_S'' G_o \\
G(P_L - H(P_L - P_H)) > G_o(P_L - H''(P_L - P_H)) \\
G(P_L - \Omega[G(P_L - P_H)](P_L - P_H)) > G_o(P_L - \Omega[G_o(P_L - P_H)](P_L - P_H))
\end{aligned}
$$

It is clear that condition $P_A(t = pre) > P_A(t = post)$ depends critically on the value of G_o and how this affect the driver's likelihood of opposing a high level of resistance. Perhaps, a more realistic setup for this period is assuming that declining in G was quite substantial and in most cases, $G_o = 0$, almost eliminating the incentives to attack a driver.

Alternatively, we can think that the introduction of the fixed-salary policy along with the elimination of cash as a payment mechanism modified the driver's choice problem. During this period, they can directly affect the probability of attack P_A by setting offender's expected reward $G = G_o$. I assume that drivers know offenders' probability of attack structure, which is given by $P_A \equiv \Pr[b_i < P_S G - S] \equiv \Psi(P_S G - S)$.

Since Ψ is an increasing function, an equivalent problem for driver's choice during the post-reform period is:

$$
\begin{aligned}
\underset{G_o}{\text{minimize}} \quad & f(G_o) = G_o \times P_S(G_o) \\
\text{subject to} \quad & G_o \geq 0
\end{aligned}
$$

Since $P_S(G_o) \in [p_h, p_l]$ and assuming that conditions for parameters $0 < p_l < 1$ and $0 < p_h < 1$ hold, we have that $0 < P_S(G_o) < 1$. In that case, the optimum solution for drivers is carrying no cash: $G_o = 0$, which minimizes the probability of being victimized.

More generally, optimum candidate values of G_o are:

$$G_o^* = \begin{cases} 0, & \text{or} \\ \frac{P_S(G)}{-P_S'(G)} = \frac{p_l-(p_l-p_h)\Omega((p_l-p_h)G_o}{(p_l-p_h)^2\Omega'((p_l-p_h)G_o)}, & \end{cases} \tag{15}$$

$G_o^* = 0$ represents a global minimum while $G_o^* = \frac{P_S(G)}{-P_S'(G)}$ represents a local optimum that may exist depending on the specific functional form of the empirical distribution $\Omega(.)$. We can see that when $G_o^* = \frac{P_S(G)}{-P_S'(G)}$, the value of the objective function is $f(G_o^*) = G_o^* P_S(G_o^*) > 0$; $\forall\ G_o^* > 0$. A more detailed expression is given by (16):

$$f(G_o^*) = G_o^* \times P_S(G_o^*) = \frac{[p_l - (p_l - p_h)\Omega((p_l - p_h)]^2}{(p_l - p_h)^2\Omega'((p_l - p_h)G_o)} > 0 \tag{16}$$

B.2 Model 2. Endogenous Determination of the Probability of Attacking

Here I describe the theoretical responses by assuming a slightly different model as the one presented in the paper. The main difference is that drivers decide in advance whether to oppose a high or low level of resistance. One advantage of this specification is that allows us to model how driver's decision is affected by the probability of being attacked. In this case, driver's decision can be characterized by:

$$H \equiv \Pr[U_H > U_L] = \Pr[c_i < P_A(P_L - P_H)G_d] = \Omega[P_A(P_L - P_H)G_d] \tag{17}$$

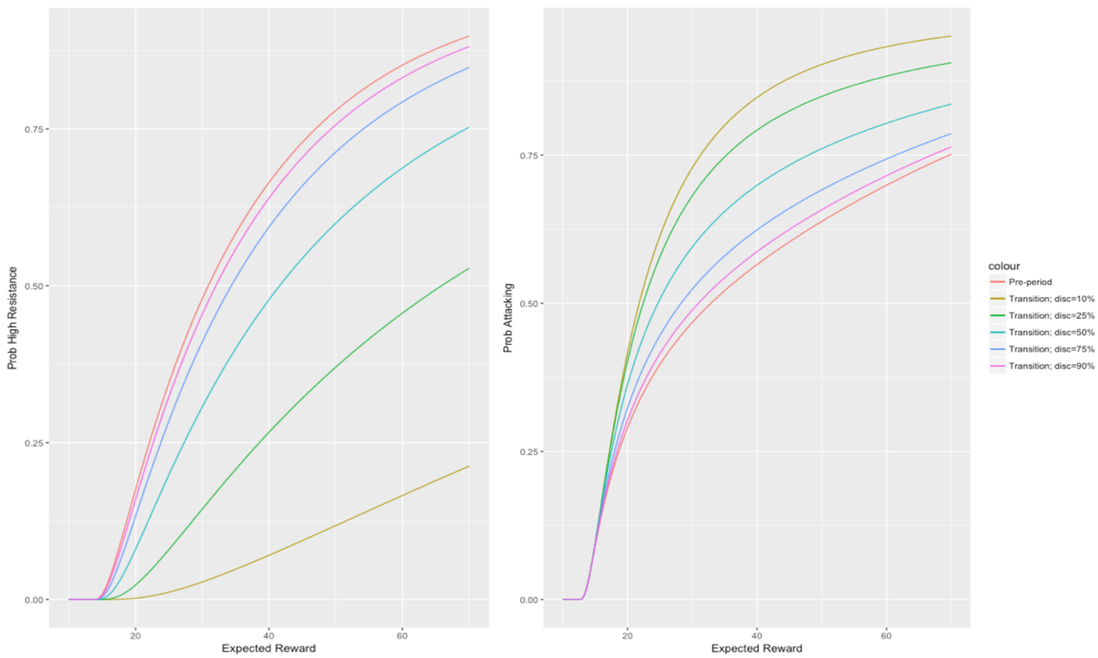
Offender's decision choice is the same as the main model, but computation of P_A can no longer be determined by simply analyzing offender's decision choice parameters. Combining both decision rules, we can solve for P_A using the following implicit equation:

Solve implicit equation for P_A:

$$\begin{aligned} P_A &= \Psi[P_S G - S] \\ &= \Psi[(P_H H + P_L(1 - H)) \times G - S] \\ &= \Psi[(P_H H(P_A, G) + P_L(1 - H(P_A, G))) \times G - S] \\ &= \Psi[(P_H \Omega[P_A(P_L - P_H)G_d] + P_L(1 - \Omega[P_A(P_L - P_H)G_d])) \times G - S] \\ &= \Psi[(P_L - (P_L - P_H) \times \Omega[P_A(P_L - P_H)G_d] \times G - S] \end{aligned}$$

In order to see how this function reacts to changes in the expected reward and losses experienced during the reform, I simulate how driver's probability of resisting and offender's probability of attacking vary for different values of G. Figure 10 summarizes those responses considering five different scenarios (different discounts associated with the losses) for the transition period:

Figure 10: Probability of High Resistance and Attacking by Expected Reward



Notes: Each line connects results from solutions implicit equations in the probability of high-resistance using 10,000 different values of the expected reward (G). For each simulation, I set the parameters with the following values: $P_l = 0.8$; $P_h = .3$, $S = 10$. Disc represent different proportions of the expected reward drivers could be responsible for protecting during the transition period. I assume that C distributes log-normal (meanlog=1, sdlog=1) and B distributes log-normal (meanlog =3, sdlog=1). For the pre-reform period, I assume that $disc = 1$ which means that expected reward equals expected loses.

B.2.1 Predicting a Crime Increase in the Transition Period

Here we need to compare the solutions for P_A in the following implicit equations:
Pre-Reform period:

$$P_A = \Psi[(P_L - (P_L - P_H)\Omega[P_A(P_L - P_H)G] \times G - S] \tag{18}$$

Transition-period:

$$P'_A = \Psi[(P_L - (P_L - P_H)\Omega[P_A(P_L - P_H)G_d] \times G - S] \tag{19}$$

Since we know that $G_d < G$ we can study the particular conditions for finding an equilibrium for each period. Comparing P_A and P'_A, we can see that the only possible predicted equilibrium is that $P_A < P'_A$. I analyze all three possibilities in detail:

1. P_A cannot be greater than P'_A. The proof is direct: If $P_A > P'_A$, we need that $GP_A < G_d P'_A$ which means that $P_A \frac{G}{G_d} < P'_A$, but since $\frac{G}{G_d} > 1$ we can rewrite the condition as $P'_A > P_A \frac{G}{G_d} > P_A$, which is a contradiction.

2. P_A cannot be equal to P'_A. Again, the proof is direct: If $P_A = P'_A$, we need that $GP_A = G_d P'_A$ which cannot be true since we know that $G_d < G$.

3. $P_A < P'_A$ represents the only possible prediction for the equilibrium levels between pre and transition period. Interestingly, under this setting, it imposes also a limit on the extent of variation in the probability of attacking. $P_A < P'_A \Leftrightarrow GP_A > G_d P'_A$ which can be re written as $P_A \frac{G}{G_d} > P'_A$. This is a reasonable prediction of the model: to some extent, it limits the growth of attacks in the transition period due to the fact that, although bus drivers have reduced their protection level they still care about the level of risk they are being exposed to.

Alternatively, we can analyze figure 10. We can compare $P_A(t = pre) > P_A(t = Post)$ by simply looking at for every level of possible expected reward, the lower is the amount the driver is responsible for, the lower the resistance level, and the higher the probability of being attacked.

B.2.2 Predicting Less Crime in the Post-Reform Period

Here we need to compare the solutions for P_A in the following implicit equations:
Pre-Reform period:

$$P_A = \Psi[(P_L - (P_L - P_H)\Omega[P_A(P_L - P_H))G_d] \times G - S] \tag{20}$$

Post-period:

$$P''_A = \Psi[(P_L - (P_L - P_H)\Omega[P_A(P_L - P_H))G_o] \times G_o - S] \tag{21}$$

where $G_o << G$. Then, the condition for a reduction in overall crime activity will depend on:

$$P_A > P_A''$$
$$(P_L - (P_L - P_H)\Omega[P_A(P_L - P_H)G] \times G > (P_L - (P_L - P_H)\Omega[P_A''(P_L - P_H)G_o] \times G_o$$

Thus, the condition for less crime in the post-reform period can be finally written as:

$$(G - G_o)P_L > (P_L - P_H)(\Omega[(P_L - P_H)P_A G] - \Omega[(P_L - P_H)P_A'' G_o] \quad (22)$$

for low values of $G_o \approx 0$ condition (22) is satisfied since is equivalent to $P_L > (P_L - P_H) \times \Omega[(P_L - P_H)P_A G]$ which must be true.

B.3 Model 3. Offender's Weapon Choice

In this case, I analyze whether the likelihood of using a particular weapon is affected by the variation on drivers and potential offenders' incentives. I modify the basic parameters of the model taking into account how they change according to a particular weapon. Finally, I incorporate an additional random component m which captures the moral aversion (cost) of using a more lethal weapon when attacking a driver. For simplification, I consider only two possible weapons: firearm and knife.

In this case, bus drivers decide their level of resistance opposed to an eventual attack based on the particular weapon used by the offender. In this case, the cost of opposing a high level of resistance represents their idiosyncratic disposition to resist an attack with a particular weapon. In that sense, we can separately analyze the chances of adopting a high-resistance strategy associated with each weapon $w = \{k, f\}$:

$$H_F = \Pr[H|weapon = F] = \Pr[c_i < (P_{LF} - P_{HF})G] \quad (23)$$

$$H_K = \Pr[H|weapon = K] = \Pr[c_i < (P_{LK} - P_{HK})G] \quad (24)$$

Where $P_{HK}, P_{LK}, P_{HF}, P_{LF}$ are parameters. Thus, the probability of being high-resistance is different for each type of weapon. As a result, now potential offenders have probability of being successful in the attack based on the weapon used:

$$P_{SF} = P_{HF}H_F + P_{LF}(1 - H_F) \quad (25)$$

$$P_{SK} = P_{HK}H_K + P_{LK}(1 - H_K) \quad (26)$$

From the offender's point of view, under this setting we have just incorporated some subscripts on the utility associated with attacking with a particular weapon. $U(weapon = w) = P_{SW}G - S_W$. We can further incorporate a term m_i which measures offender's moral aversion to using a lethal weapon. We can assume that m_i distributes with some empirical distribution $d(\Theta)$. Thus, under this setting, an offender chooses to attack with a firearm based on the following condition:

$$\Pr[w = Firearm] = \Pr[U_F > U_K] = \Pr[m_i < G(P_{SF}(G_{BD})) - P_{SK}(G_{BD}) - S_F + S_K] \tag{27}$$

We can compare that expression for the pre-reform and transition period:

Pre-Reform period:

$$\Pr[U_F > U_K | t = pre] = \Theta[G(P_{SF}(G) - P_{SK}(G)) - S_F + S_K] \tag{28}$$

Transition-period:

$$\Pr[U_F > U_K | t = tra] = \Theta[G(P_{SF}(G_d) - P_{SK}(G_d)) - S_F + S_K] \tag{29}$$

Now, the condition for a reduction in the propensity to use a firearm in the transition period is:

$$P_{SF}(G_d) - P_{SK}(G_d) < P_{SF}(G) - P_{SK}(G) \tag{30}$$

We can re-write that condition as:

$$P_{SF}(G_d) - P_{SF}(G) < P_{SK}(G_d) - P_{SK}(G) \tag{31}$$

Interestingly, we know that those two quantities are positive since for any weapon w, the condition:

$$P_{SW}(G_d) > P_{SW}(G) \tag{32}$$

holds. This is a direct result of the decrease in the driver's propensity to resist in the transition period.

Thus, condition (32) holds if chances for being successful when attacking with a knife vary more over time relative to attacking with a firearm. In a sense that expression holds if the return of using a particular weapon is more sensitive to a variation in G.

We can explicitly incorporate $G_d < G$. Let's call $\Delta_w = P_{HW} - P_{LW}$ for each particular weapon w. Thus, the condition for a decrease in the proportion of firearm-related incidents is:

$$\begin{gathered}
P_{SF}(G_d) - P_{SF}(G)) < P_{SK}(G_d) - P_{SK}(G) \\
H_F(G)\Delta_F - H_F(G_d)\Delta_F + P_L - P_L < H_K(G)\Delta_K - H_K(G_d)\Delta_K + P_L - P_L \\
\Delta_F[H_F(G) - H_F(G_d)] < \Delta_K[H_K(G) - H_K(G_d)]
\end{gathered}$$

Moreover, we know by assumption that $(P_{LF} - P_{HF}) < (P_{LK} - P_{HK})$, which simplifies the condition to:

$$H_F(G) - H_F(G_d) < H_K(G) - H_K(G_d)$$
$$or$$
$$H_K(G_d) - H_F(G_d) < H_K(G) - H_F(G)$$

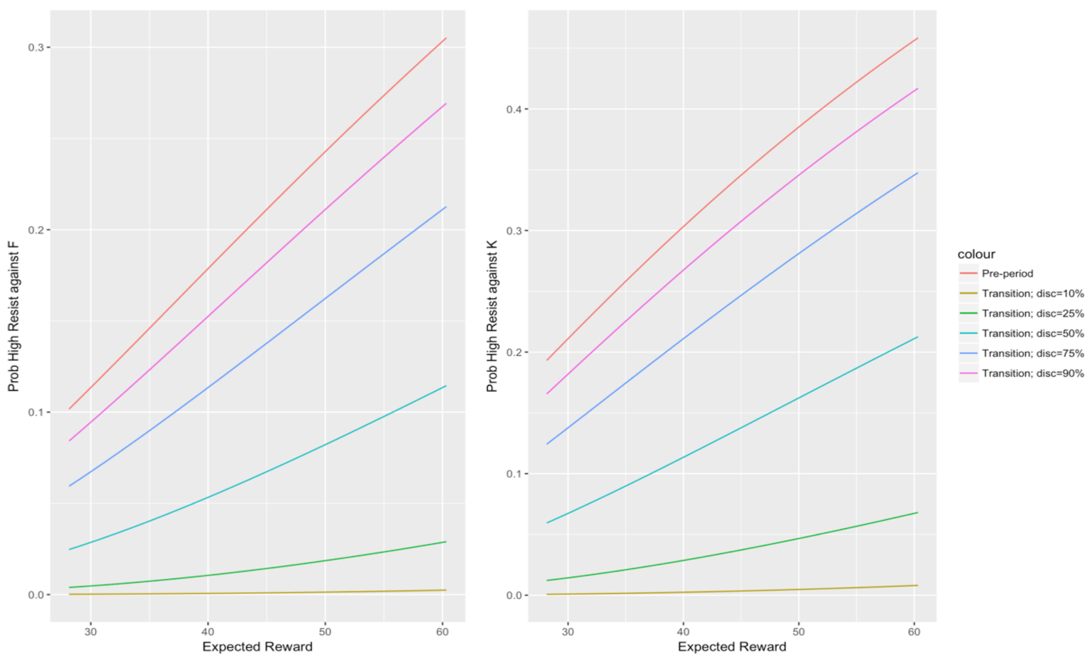
This condition can be empirically tested [23].

Although whether (32) holds is an empirical question, we can discuss how likely that condition is satisfied in the case of our particular setting. It is plausible to think that the variation in driver's likelihood to resist when attacked with a firearm is close to zero regardless of the amount of cash available. This means that $H_F(G) - H_F(G_d) \approx 0$. On the other hand, we can think that during the transition period driver's likelihood to resist when attacked by a knife unambiguously decreased. This means that $H_K(G) - H_K(G_d) > 0$. In that case, condition (32) is clearly satisfied.

Finally, to further discuss this prediction, I include simulations of the model based on different values of the expected reward. These figures allow us to clearly see that probability of attacking with a firearm decreased in the transition period.

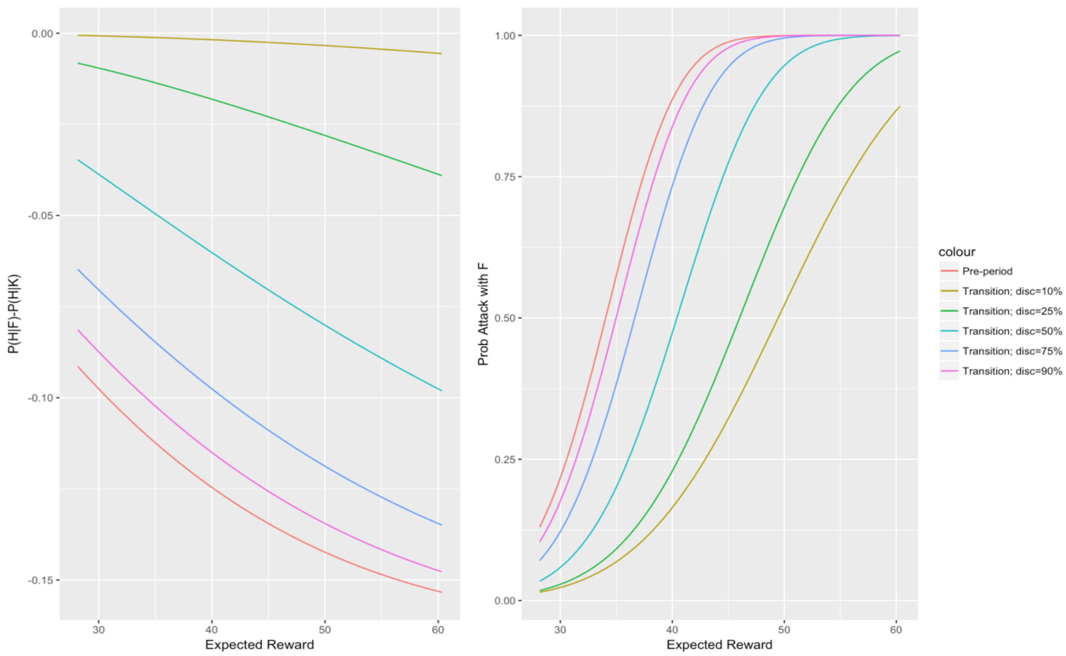
[23]If we imposed some specific restrictions in the density function, we can analyze under which weapon the response in terms of driver's probability of resist is higher. In that sense, condition for observing a decrease in the firearm-related incidents during the transition period is: $H'_F(G) < H'_K(G)$. We can calculate that as: $dH/dG = \Omega'[(P_L - P_H)G](P_L - P_H) > 0$. Rewriting our condition, we have: $\Omega'[(P_{LF} - P_{HF})G](P_{LF} - P_{HF}) < \Omega'[(P_{LK} - P_{HK})G](P_{LK} - P_{HK})$ or simply $\Omega'[(P_{LF} - P_{HF})G] < \Omega'[(P_{LK} - P_{HK})G]$. which is always true for any region where the density function is increasing since $(P_{LF} - P_{HF}) < (P_{LK} - P_{HK})$.

Figure 11: Probability of Resisting by Expected Reward: Weapon = Firearm or Knife



Notes: Each line connects results from solutions implicit equations in driver's probability to resist using 10,000 different values of the expected reward (G). For each simulation, I set the parameters with the following values: $P_{lf} = 0.8$; $P_{lk} = 0.6$; $P_{hf} = 0.7$; $P_{hk} = 0.4$; $S_f = 30$; $S_k = 25$; $G = 60$. Disc represent different proportions of the expected reward drivers could be responsible for protecting during the transition period. I assume that C distributes log-normal (meanlog=3, sdlog=1) and B distributes log-normal (meanlog =B, sdlog=1). For the pre-reform period, I assume that $disc = 1$, which means that expected reward equals expected loses

Figure 12: Differential Probability of Resisting and Attacking by Expected Reward



Notes: Each line connects results from solutions implicit equations in offender's probability of attacking using 10,000 different values of the expected reward (G). For each simulation, I set the parameters with the following values: $P_{lf} = 0.8$; $P_{lk} = 0.6$; $P_{hf} = 0.7$; $P_{hk} = 0.4$; $S_f = 30$; $S_k = 25$; $G = 60$. Disc represent different proportions of the expected reward drivers could be responsible for protecting during the transition period. I assume that C distributes log-normal (meanlog=3, sdlog=1) and B distributes log-normal (meanlog =B, sdlog=1). For the pre-reform period, I assume that disc=1, which means that expected reward equals expected losses.

B.4 Drivers Resistance Level Implicit in Our Findings

As we have seen in the previous sections, potential offender's and victim's reaction functions are described by the following equations:

$$\begin{aligned}P_A =& \Phi(P_S G_O) - S)\\ P_S =& - H(p_L - p_H) + p_L = -H\Delta_p + p_L\\ H =& \Psi(\Delta_p G_D)\end{aligned}$$

Based on our empirical findings, we have that $P_A(t = tra) = 2.5 \times P_A(t = pre)$. If we consider that offender's heterogeneity in terms of sanction costs is captured by their opportunity costs, we can disregard S from equations B.4. Further, if we assume that $b_i \sim U(0,1)$, we can rewrite P_A for the pre-reform and transition period as:

$$\begin{aligned}P_A(t = pre) =& P_A = P_S G_O\\ P_A(t = tra) =& P'_A = P'_S G_O\end{aligned}$$

Then it is easy to show that $2.5 \times P_S = P'_S$. Finally, if we consider that offender's probability of success is one when drivers do not present any resistance $p_L = 1$, and that given the change of incentives for drivers the probability of adopting a high resistance strategy for each period can be approximated as $\Delta_p \times G_D >> 0 \Leftrightarrow H \approx 1$ and $\Delta_p \times G'_D \approx 0 \Leftrightarrow H \approx 0$. Therefore, we have that $P_S = p_H$ and $P'_S = 1$, which substituting in the first equation of this paragraph finally implies that $p_H = 1/2.5 = 0.4$.

Table 11: Interrupted Time Series Estimates: Robbery on Buses

LogOLS	1 Noncash	2 Noncash	3 Cash	4 Cash
Transition	0.183**	0.0699	0.913***	0.915***
	(0.060)	(0.070)	(0.090)	(0.090)
Post	0.0935	-0.0106	-1.108***	-1.021***
	(0.050)	(0.060)	(0.080)	(0.090)
Month FE	Yes	Yes	Yes	Yes
Robb_PS	No	Yes	No	Yes
N	314	314	301	301
R-sq	0.275	0.365	0.759	0.773

Notes: Coefficients are calculated using interrupted time series in each crime category. $Robb_{PS}$ represents robberies in the same crime category (cash- or noncash-related incidents). Robust standard errors are reported in parentheses.* p<0.05, ** p<0.01, *** p<0.001.

Table 12: Interrupted Time Series Estimates: Robbery on Buses

Poisson	1 Noncash	2 Noncash	3 Cash	4 Cash
Transition	0.144*	0.102	0.956***	0.947***
	(0.060)	(0.060)	(0.060)	(0.060)
Post	0.0888	0.0483	-1.101***	-1.030***
	(0.050)	(0.060)	(0.070)	(0.070)
Month FE	Yes	Yes	Yes	Yes
Robb_PS	No	Yes	No	Yes
N	314	314	314	314
Pseudo R-sq	0.083	0.086	0.623	0.628

Notes: Coefficients are calculated using interrupted time-series on each crime category. $Robb_{PS}$ represents robberies in the same crime category (cash- or noncash-related incidents). Robust standard errors are reported in parentheses.* p<0.05, ** p<0.01, *** p<0.001.

Table 13: Difference-in-Differences and Triple Differences Estimates: Robbery

Log-OLS	1 DD	2 DD	3 DDD	4 DDD
Trans x Cash (x Bus)	0.730***	0.730***	0.866***	0.866***
	(0.100)	(0.100)	(0.110)	(0.110)
Post x Cash (x Bus)	-1.206***	-1.016***	-0.921***	-0.788***
	(0.100)	(0.100)	(0.110)	(0.110)
N	615	413	1243	829
R-sq	0.738	0.745	0.963	0.971

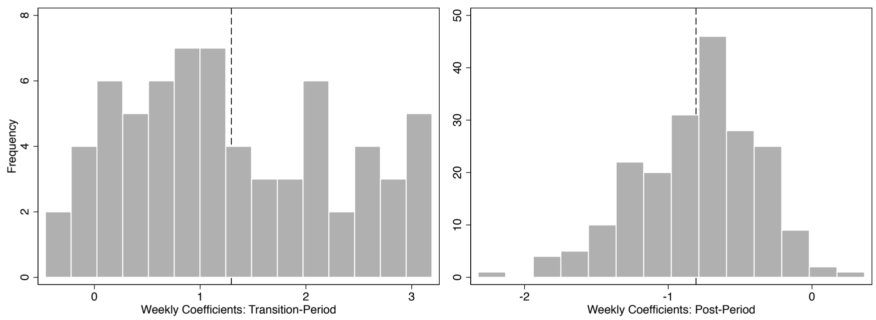
Notes: Coefficients from DD and DDD regressions including monthly fixed effects. Columns two and four consider a restricted sample (Year < 2009). Robust standard errors are reported in parentheses.* p<0.05, ** p<0.01, *** p<0.001.

Table 14: Difference-in-Differences and Triple Differences Estimates: Robbery

Poisson	1 DD	2 DD	3 DDD	4 DDD
Trans x Cash (x Bus)	0.740***	0.740***	0.882***	0.882***
	(0.090)	(0.080)	(0.100)	(0.100)
Post x Cash (x Bus)	-1.232***	-1.020***	-0.954***	-0.795***
	(0.080)	(0.090)	(0.100)	(0.100)
N	628	416	1256	832
Pseudo R-sq	0.175	0.164	0.949	0.954

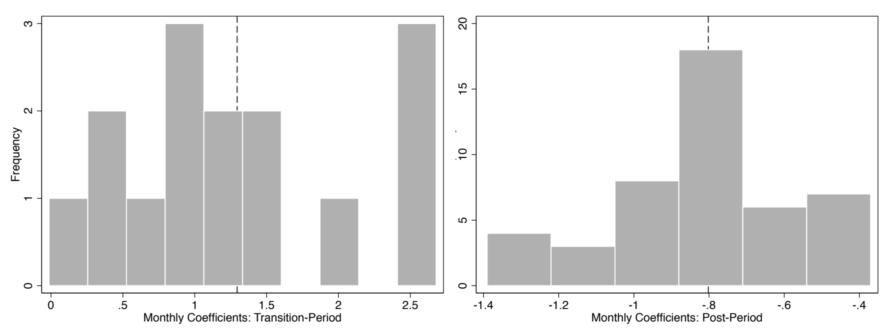
Notes: Coefficients from DD and DDD regressions including monthly fixed effects. Columns two and four consider a restricted sample (Year < 2009). Robust standard errors are reported in parentheses.* p<0.05, ** p<0.01, *** p<0.001.

Figure 13: Histogram: Density of the Event-Study Coefficients, 2005-2010



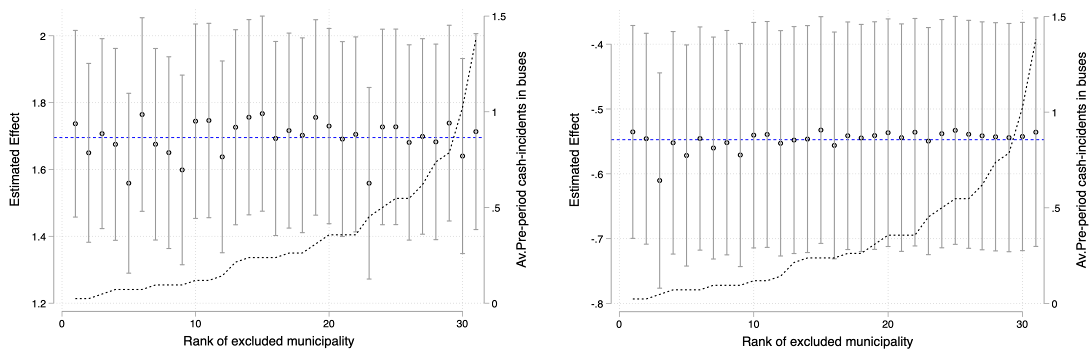
Notes: Figures represent the density function of the interacted coefficients δ of equation (11) using weekly indicators. Right figure displays the density function of coefficients during the transition period. Left figure displays the density function of coefficients during the post-reform period. Vertical dashed lines show the value of the coefficient from regression 9.

Figure 14: Histogram: Density of the Event-Study Coefficients, 2005-2010



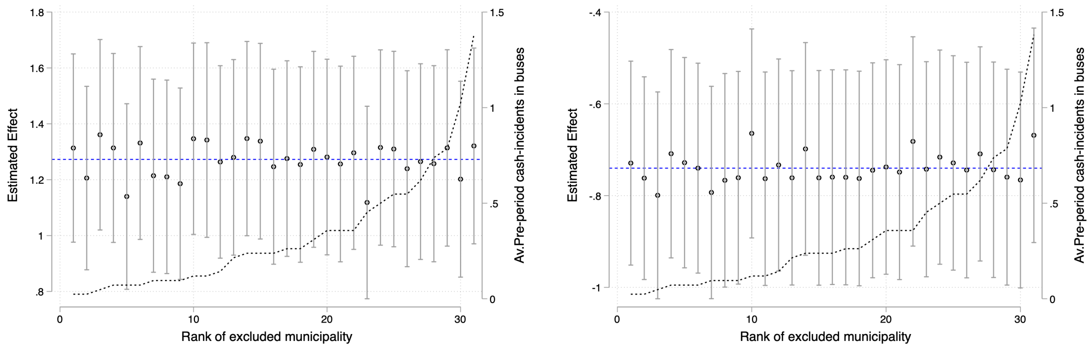
Notes: Figures represent the density function of the interacted coefficients δ of equation (11) using monthly indicators. Right figure displays the density function of coefficients during the transition period. Left figure displays the density function of coefficients during the post-reform period. Vertical dashed lines show the value of the coefficient from regression 9.

Figure 15: Robustness of Estimated Treatment Effect to Dropping Municipalities: Interrupted Time Series



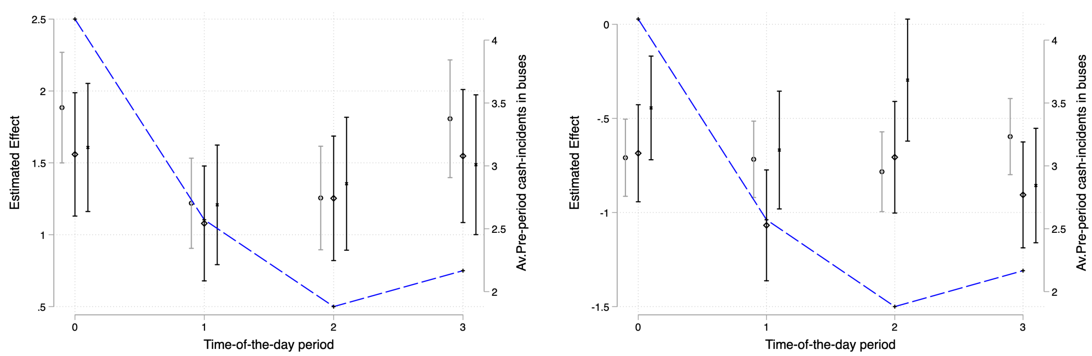
Notes: Figure shows interrupted time series coefficients of separate unweighted regressions using municipality-level panel data but excluding one municipality at a time. Left-side figure shows estimates for the transition period while post-policy period estimates are plotted on the right side. All regressions include municipality by month fixed effects, and standard errors are clustered at the municipality level. 95% confidence intervals are included. Municipalities excluded from the sample are indicated in the horizontal axis which are ranked by the level of incidents during the pre-policy period. Black dashed blue line connects average weekly level of cash-related robberies on buses during the pre-policy period, and references values are indicated in the secondary right-side vertical axis.

Figure 16: Robustness of Estimated Treatment Effect to Dropping Municipalities: Triple Differences



Notes: Figure shows triple differences coefficients of separate unweighted regressions using municipality-level panel data but excluding one municipality at a time. Left-side figure shows estimates for the transition period while post-policy period estimates are plotted at the right side. All regressions include municipality by month fixed effects and standard errors are clustered at the municipality level. 95% confidence intervals are included. Municipalities excluded from the sample are indicated in the horizontal axis which are ranked by the level of incidents during the pre-policy period. Black-dashed blue line connects average weekly level of cash-related robberies on buses during the pre-policy period, and references values are indicated in the secondary right-side vertical axis.

Figure 17: Robustness of Estimated Treatment Effect to Time of Day



Notes: Figure shows coefficients estimated by running separate regressions for each time-period of the day. 95% confidence intervals are included for each estimate. Left-side figure shows estimates for the transition period while post-policy period estimates are plotted on the right side. Coefficients estimated using different approaches: interrupted time series (circle), difference-in-differences (diamond), and triple differences (x). Dashed blue line connects weekly average level of cash-related robberies on buses during the pre-policy period, and references values are indicated in the secondary right-side vertical axis. Time of day is sorted as follows: 5PM-9.59 PM (0), 10PM-5.59AM (1), 6AM-10.59AM (2), 11AM-4.59 PM hrs (3)

Table 15: Newey-West Estimates: Proportion of Firearm Robberies on Buses, Cash

	1	2	3	4	5	6
Transition	-0.0877**	-0.0877***	-0.0877***	-0.0903**	-0.0903***	-0.0903***
	(0.026)	(0.018)	(0.013)	(0.028)	(0.017)	(0.013)
Post-Reform	-0.0903**	-0.0903**	-0.0903**	-0.0980**	-0.0980**	-0.0980**
	(0.029)	(0.028)	(0.027)	(0.031)	(0.034)	(0.033)
Month FE	N	N	N	Y	Y	Y
YEAR<=2008	N	N	N	N	N	N
# Lags	1	12	24	1	12	24
N	72	72	72	72	72	72

Notes: Newey-West coefficients are calculated using interrupted time-series on each crime category. Robust standard errors are reported in parentheses.* p<0.05, ** p<0.01, *** p<0.001.

Table 16: Newey-West Estimates: Proportion of Firearm Robberies on Buses, Cash

	7	8	9	10	11	12
Transition	-0.0877**	-0.0877***	-0.0877***	-0.0781*	-0.0781**	-0.0781***
	(0.026)	(0.019)	(0.013)	(0.031)	(0.026)	(0.018)
Post-Reform	-0.0332	-0.0332	-0.0332*	-0.0318	-0.0318	-0.0318*
	(0.028)	(0.019)	(0.013)	(0.031)	(0.026)	(0.015)
Month FE	N	N	N	Y	Y	Y
YEAR<=2008	Y	Y	Y	Y	Y	Y
# Lags	1	12	24	1	12	24
N	48	48	48	48	48	48

Notes: Newey-West coefficients are calculated using interrupted time-series on each crime category. Robust standard errors are reported in parentheses.* p<0.05, ** p<0.01, *** p<0.001.

Table 17: Interrupted Time Series Estimates: Proportion of Firearm Incidents on Buses, Noncash Robbery

	1	2	3	4
Transition	-0.0428	-0.0471*	-0.0428	-0.0434
	(0.023)	(0.023)	(0.023)	(0.024)
Post-Reform	0.0342	0.0319	0.0438	0.0422
	(0.022)	(0.021)	(0.025)	(0.028)
Month FE	N	Y	N	Y
YEAR<=2008	N	N	Y	Y
N	72	72	48	48
Pseudo R-sq	0.201	0.345	0.266	0.385

Notes: Coefficients are calculated using interrupted time-series in each crime category. Robust standard errors are reported in parentheses.* p<0.05, ** p<0.01, *** p<0.001.

Table 18: Proportion of Victims with Some Injury by Weapon Used: Noncash Robbery

Period	Pre		Transition		Post	
Weapon	Prop.S.I	# [Inc/M]	Prop.S.I	# [Inc/M]	Prop.S.I	# [Inc/M]
No Weapon	0.077	1.3	0.120	1.7	0.306	1.3
Firearm	0.113	12.4	0.089	11.9	0.100	17.8
knife	0.038	23.5	0.078	33.1	0.096	29.2
Stick	0.412	1.7	0.242	2.2	0.356	2.5
Threat	0.250	8.4	0.247	14.6	0.376	13.1
Other	0.129	3.1	0.108	4.9	0.067	4.8
Total [Inc/Month]	50		68		69	

Notes: Prop.S.I shows the proportion of victims that report some injury in each period. For display purposes I include a column with the number of incidents per month reported in each weapon-category for each period.