Essays on the Economics of Urban Crime

By

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A dissertation submitted in partial satisfaction of the requirements for the degree of Doctor of Philosophy in

Public Policy in the

Graduate Division of the

University of California, Berkeley

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Spring 2018
Essays on the Economics of Urban Crime

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Abstract

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This dissertation focuses on what determines crime and victimization in the urban space. The theoretical basis of this work strongly rests on the contributions of Gary Becker and Ronald V. Clarke to the crime literature. Chapter one offers a brief and selected overview of many important contributions in the economics of crime literature. I focus on some particular puzzles and the kind of solutions that have been offered in the last fifty years where the understanding regarding the role of prisons as a crime-control policy tool is critically assessed. I emphasize the complexity and multi-causal nature of crime as a way to motivate the theoretical and empirical contributions of chapters two and three. In the following chapters I pay special attention on how criminal activity reacts to changes in incentives or situational factors under different theoretical and empirical settings. Chapter two is devoted to understand criminal activity in the public transportation sector which represents a salient place where criminal activity takes place. I incorporate a simple model of offenders and victim’s interactions to describe how victim’s behavior reacts and determines the set of criminal opportunities available for potential offenders. Empirically, I exploit a set of subsequent reforms in the public transportation system where variations to driver’s incentives as well as the availability of cash substantially altered the amount and the nature of criminal activity observed. In chapter three, jointly written with Kenzo Asahi, we study the effect of a particular situational factor such as ambient light on crime. In both cases, the evidence I find supports the relevance of incentives. I identify specific policy changes or situational deviations whose effects in terms of criminal victimization can be equivalent to enormous public policy interventions in terms of prosecution. All findings presented in this dissertation attempts to enlarge the growing body of scientific understanding regarding criminal activity in urban areas.
To Gabi

and our children, Elisa and Beltrán
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Acknowledgments

I would not have been able to finish this dissertation without the help of numerous people who contributed in many different and important ways. I extend my deepest gratitude to all of them in the following lines.

To my dissertation committee Steven Raphael, Amy Lerman, Michael Anderson and Rucker Johnson. You all have been a great source of intellectual inspiration. Special thanks to my main advisor Steve whose wisdom and generosity I would like to replicate in the future.

I would also like to acknowledge helpful comments from the following individuals who have provided feedback on individual chapters and savy advise during my graduate studies: Juan Pablo Atal, Daniel Baker, José Miguel Benavente, Phil Cook, Alain De Janvry, John Ellwood, Avi Feller, Lee Friedman, Hilary Hoynes, Carola Jorquera, Supreet Kaur, David Kirp, Carlos Melo, Ted Miguel, Juan Carlos Muñoz, Krista Ruffini, Eugene Smolensky, and participants at multiple seminars at Berkeley, the 7th AlCapone meeting, and the 9th Transatlantic workshop in economics of crime. Especial thanks to my colleagues Krista and Kenzo, for the privilege of having worked with you.

I have received financial support from different sources that I would also want to thank: Conicyt - Becas Chile, Pontificia Universidad Catolica, the Berkeley Center for Latin American Studies, and the California Policy Lab.

Thanks to my Ph.D fellow friends, especially Daniel Baker, and my M.P.P friends Vivi, Fernanda, Kiko, Chelsea, Tim and Swatie.

To all my friends, a los de siempre y los que se nos aparecieron en el Bay Area. Y como esta lista es muy larga la quisiera enumerar como sigue: Los del Chile Seminar, los que organizamos The Challenge of Inclusive Development, Garra Latina futbol team y con quienes compartí otros tantos encuentros gratuitos en Albany, Berkeley, Davis, Menlo Park, San Francisco, Santa Cruz y Stanford.

A la extensa red que nos ha ayudado a criar a nuestros hijos: Dinha, Mila, Vero, Graca, Emenilda, Elisa-teacher, Amie, Tami, Fang, Simone, y en especial sus cuatro abuelos. To all the people that makes constantly beautiful the communities of Warring St, Albany and Solano Av., especial thanks to the workers of Cafe Strada, Free Speech Cafe y otros de tanta calidad humana como Luis y Saul. Quiero también agradecer a mis hermanos y, en especial, a mis viejos y al Pancho.

And here is the part where words will certainly fall short.

The most important factor has been the endearing help of my family. Because of you I have the best memories of Berkeley, in spite of the very dramatic political times we are living in. My wife Gabi, who was the first one accepted at Cal, has shown me that with careful and devoted passion there is no excuses to find the right thing to do. My children, have been the perfect reason to responsibly procrastinate my everyday student duties. To be fair, they could not have been a better support for a student parent either: Elisa enthusiastically attended graduate classes many times, and Beltrán was patient enough to postpone his birth right after my Ph.D qualifying examination. I cannot tell how much I have enjoyed
this period with you. Overall, you have been the most notable way of feeling home far away from my country.

Por todo eso y mucho más, el más especial de los agradecimientos a Gabi. No podría haber imaginado una mejor esposa y compañera.
This dissertation focuses on what determines crime and victimization in the urban space. The theoretical basis of this work strongly rests on the contributions of Gary Becker and Ronald V. Clarke to the crime literature. I pay special attention on how criminal activity reacts to changes in incentives or situational factors. A salient feature in this regard has to do with how victim’s behavior reacts and determines the set of criminal opportunities available for potential offenders. The evidence I find supports the relevance of incentives, and I identify specific policy changes or situational deviations whose effects in terms of criminal victimization can be equivalent to enormous public policy interventions in terms of prosecution. All findings presented in this dissertation attempts to enlarge the growing body of scientific understanding regarding criminal activity in urban areas.

In the first chapter I present a brief overview of the economics of crime literature. Basically, I discuss a set of recent empirical findings that overall reinforce the notion of criminal activity as a complex and multi-causal phenomenon. I describe a set of common empirical challenges, and briefly review some specific solutions that have been offered in the literature. I pay particular attention to one of the most salient puzzles in the field which is why crime rates have dramatically decreased in the last twenty-five years in almost all northern-western democratic nations. Finally, I offer some specific avenues for future research that are strictly related to the findings of the two following chapters.

In the second chapter I study robberies in the public transport system, and the implications of a change in the way the bus system is organized. In an attempt to rationalize and better integrate public transportation in Chile the bus system suffered two important shocks that had strong effects in crime: change in drivers’ salary policy that alter their incentives to harm a common criminal target such as the money collected in the fare collection boxes (transition period); and the implementation of a debit card that fully eradicates of the use of cash (post-policy period). To better understand the possible effects of the transition period, I model crime rates as a function of the interaction between potential offenders and victims. This is an interesting feature of this project: unlike most of the empirical work in the economics of crime pays special attention to the role of victims who bears the costs of victimization but also a considerable portion of the costs devoted to prevent criminal activity. I also show how victim’s behavior can alter not only the level but the nature of the observed criminal activity.

Using the pre-reform period as a benchmark I found that during the transition period crime increased by 150% from 12 incidents to 28 incidents per week. This result is robust to three different specifications including an event study design that accounts for any specific secular trend. Relative to available estimates in the literature this finding suggests that private behavior is an important omitted variable in understanding victimization. Considering that available empirical evidence suggests a crime-police elasticity estimate of -0.3 (Di Tella and Schargrodsky, 2004), I estimate that the overall crime reduction associated with a high protection strategy adopted by drivers would be compensated by a 200% increase in police presence.

Interestingly, although these results suggest that victims can do a lot to prevent criminals from offending, this could of course come at a very high personal cost. I find that during the
pre-reform level of a relatively low crime rate I also notice that drivers were exposed to a higher level of violence conditioning on being robbed. Specifically, I find a higher proportion of attacks using a less lethal weapon at the same time when drivers drastically reduced their level of resistance. Further, this finding is reinforced by the fact that conditioning on being attacked with a particular weapon, drivers were less likely to report some injuries during the transition period, and that variation was larger for less lethal weapons.

Finally, using the same set of empirical strategies, I find a consistent reduction in non-cash crime related incidents following the implementation of a cashless debit card in the post-policy period. This finding is not only relevant for policymakers that want to make public transportation safer but presents a promising avenue for future research regarding how a reduction in the use of cash can lead to a decline in crime.

The third chapter, written jointly with Kenzo Asahi, provides new estimates of the effect of ambient light on criminal activity. In spite of the common belief that the darkness offers an environment conducive to crime empirical estimates has proven to be difficult. Theory suggests different channels through which ambient light may affect crime and the overall effect is ambiguous. In this chapter, we take advantage of a plausible exogenous variation in ambient light and evaluate how it affects the overall level of criminal activity.

We take advantage of a large administrative database provided by the Chilean national police (approx. 2 million incidents), and the exogenous variation in ambient light during different hours of the day imposed by the Daylight-Saving Time policy (DST). We implement different research strategies relying on two distinct identification assumptions. We first use a regression discontinuity design that relies on the fact that DST imposes a sharp variation in ambient light at specific hours of the day. In addition, we compare those estimates with a Difference in Difference approach that take advantages of a delay on the implementation of the policy. In this case we analyze, how the level of criminal activity changes when DST is in place during the same period of the calendar year.

Considering both DST transitions, we find that between 7-9PM a one-hour increase (decrease) in ambient light causes a 20% decrease (increase) in property crimes. That particular response is mostly driven by robbery which is consistent with the fact that is the crime-category better reported in terms of the time of the incident. Finally, we find no significant effects at any other hour of the day which reinforces that our results are driven by the sharp variation in ambient light imposed by the DST policy.

Our results are remarkably consistent and robust under a variety of checks. Although in this case we cannot fully distinguish offender and victims behavior, our findings suggest that most of the action is driven by a supply-side reaction (e.g. potential offenders). Two complementary findings support that: (i) we did not detect a similar reaction using Metro hourly ridership data for the same period of time which suggests that the variation in crime is not driven by a change on people’s time-commuting pattern, and (ii) we find no substantial (short-term) crime temporal displacement to other period of the day.
Chapter 1

Fifty Years of Economics of Crime Literature

This dissertation presents and discusses a set of empirical findings within the economics of crime literature. An implicit claim across all chapters is the definition of crime as a complex and multi-causal phenomenon (Cook and Ludwig, 2010). Such a broad definition likely reflects the current state of knowledge in the field where a crucial goal is to find a diverse portfolio of policy options that could embrace the complexity of the phenomenon.

In this chapter I overview a selected set of findings in the economics of crime literature. I start with a brief description of two important theoretical insights provided by Becker fifty years ago. Then, I describe more recent contributions in empirical methods where the study of crime and criminal justice policy have played a salient role. In this case, I argue that researchers have not only benefited from the tools developed in other fields, but also pioneering the recent revolution in empirical methods in economics.

In section two, I describe some common challenges in the empirical study of crime and crime-control policy. I show that identifying what causes an observed variation in aggregate crime rates can be very a difficult task, but a feasible one. In order to illustrate that point I present one of the salient puzzles in the field: crime rates have decreased dramatically in the last twenty-five years in many north-western democratic countries, and we still do not know exactly why. I complement that missing piece assessing the abundant evidence regarding the specific role of prisons on that regard. In particular, I discuss the degree to which its massive expansion has been effective from a crime prevention and control perspective.

Finally, section three bridges the main results of this dissertation with the current state of the literature. I discuss their relevance towards a better understanding of the complexity of crime, as well as the possibility to offer some guidelines for future research.
1.1 Introduction

It is customary to find a reference to Gary Becker’s (1968) article in most economics of crime studies. This is one of the most cited papers in economics so any attempt to summarize its contribution may sound incomplete. But if I have to highlight a couple of features I believe the definition of crime as a choice and the formulation of a normative framework to evaluate crime control policies are among the most salient ones.

The simplest version of Becker’s model defines criminal behavior as choice made by a potential offender based on the perceived consequences of his/her actions. In a way, this formulation has stimulated a large body of theoretical work in economics to understand the complexities of crime and the criminal justice system. In addition, and relative to other approaches that emphasize the deep or social causes of crime, the idea of choice has important policy implications. At least in the short term, it defines a broader scope for action considering all factors that could potentially alter criminal behavior.

By contrast, considering the early contributions of Beccaria (1764) and Bentham (1830) the possibility of controlling crime by deterring potential offenders was far from novel among criminologists and legal scholars. In that sense, a limitation of Becker’s work and many of the subsequent studies is a lack of appreciation for the cumulative knowledge developed in several disciplines, other than economics. One of the most notable exceptions in that regard has been the development of the situational crime prevention approach pioneered by Ronald V. Clarke. His approach pays careful attention to the role of incentives as well as the particular circumstances surrounding a specific crime incident. This more explicit accounting of situational factors surrounding crime activity plays an important role in the following chapters.

But probably the most important contribution of Becker and most economists in the field is the idea that the social costs of crime are the sum of the direct costs of victimization (including the threat of victimization), and all costs associated with controlling and prevent crime. A profound consequence of that formulation is that a situation with no crime is likely far from optimal considering the eventual high costs to be incurred through crime prevention policy. A more recent extension of that argument has been underscored by Cook, Machin, et al. (2013) who highlight that the relevant question in criminal justice is not limited to what works but rather what is worthwhile.

Besides these important theoretical formulations, any assessment of the contributions of this field needs to take into account the relatively recent incorporation of sophisticated quantitative methods to analyze the causes and consequences of crime (Cook, Machin, et al., 2013). Some remarkable contributions were pioneered by Levitt in the 1990s, and subsequently followed by a large number of economists. Nowadays, it is very common to see crime-related papers in any top journal in economics which is probably true not only for its relevance in the policy arena but also for the rich set of technical contributions that most empirical approximation to this complex phenomenon demand to researchers.

The main innovation of this body of empirical work has been the use of creative research designs to address a set of endogenous relationships between aggregate crime and crime
control policies. The empirical challenge is usually given by the fact that crime and crime prevention can be simultaneously determined. In other words, crime rates are affected by law enforcement conditions which at the same time can be determined by the level criminal activity. The presence of these “feedback loops” is very common in the economics of crime literature (Cook, Machin, et al., 2013; Bushway and Reuter, 2008). According to Cook, Machin, et al. (2013), while two specific loops that have been incorporated in many econometric models, a third one that considers private prevention efforts endogenous “has been largely neglected in the economics literature” (Cook, Machin, et al., 2013, p.10). A better understanding of the empirical implications of this final loop is a central theme of this dissertation.

Two pioneering examples closely related to the first two loops identified by Cook, Machin, et al. (2013) were addressed by Steven Levitt. In one case, Levitt (1996) estimates the marginal effect of imprisonment on crime. One of the methodological challenges in that empirical endeavor is the simultaneity between those variables when using aggregate crime data. A simple comparison of incarceration and crime rates over time can hardly offer a causal effect of the former on the latter. The reason is that the observed variation in crime is likely affected not only by the causal effect of interest (the marginal effect of prison on crime) but by the fact that incarceration rate is altered by the number of people convicted which also depends on the level of crime.

Levitt’s strategy to isolate the causal effect of imprisonment on crime rates rely on a series of prison overcrowding reforms that substantially altered the prisoner population without directly affecting the level of crime. The intuition of the instrument is that although these reforms could have been precisely affected by previous levels of crime (affecting the validity of the instrument), the timing of the prison reduction induced by the court-ordered reforms is arguably exogenous. Levitt’s implied elasticity is two to three times greater than previous studies that did not account for simultaneity bias. As we discuss below, an important limitation of this article is that it does not identify the particular mechanism (incapacitation or deterrence) through which prison population affects crime. However, this is something that Levitt himself and other creative researchers have attempted to address more recently.

In 1997, Levitt publishes another pioneering study that estimates the productivity of police in reducing crime. He calls into question a number of studies that fail to detect that an increase in the number of police reduces crime. He argues that what may account for that insignificant effect is also simultaneity bias. Levitt (1997) brings a new creative way to break the simultaneous relationship. He documents that the size of police manpower tends to increase in the year prior to a municipal or state election in large US cities. The validity of this instrument (to effectively isolate the causal effect of police) relies on the fact that crime rates should not be affected by the election cycle except for the variation in the size of police force. Relative to the prior literature, and even his own OLS specification using panel data for fifty cities during 1972-1997, his IV estimates suggest much larger elasticities, especially for violent crime. Later, the significance of the estimates, and the relevance of the instrument (e.g. first stage) has been questioned in a fruitful exchange with McCrary (2002) that stimulates both the relevance of replication in empirical analysis (Poterba, 2005), and
the search for other sources of identification (Levitt, 2002; Evans and Owens, 2007).

1.2 The U.S. crime evolution puzzle

Besides the rich body of empirical evidence, the economics of crime literature still have important questions to be addressed. One of the most striking puzzles is the U.S. crime evolution. Figure 1.1 shows that both property and violent crime rates show a similar pattern with a large increase in the 1960-1990 period, and a remarkable decline after the 1990s. Levitt (2004) documents that crime fell dramatically in the United States in the 1990s, across different regions and all crime-categories, and even using the main two sources of data. More importantly, he emphasizes that these declines occurred essentially without warning.

Figure 1.1: Crime Rate Evolution in the United States 1960-2016

Notes: Own elaboration using Uniform Crime Reporting data. Crime rates are calculated as the annual number of offenses per 100,000 population.
Levitt (2004) discusses the role of ten candidate explanations and show that only four of them may account for the dramatic decline. Among the candidates that played no role or cannot account for a relevant portion of the variation he mentions the following: changing demographics; better policing strategies; gun control laws; laws allowing carrying concealed weapons; and increased use of capital punishment. According to Levitt the most relevant factors that causes the crime decline are an increase in police manpower, a dramatic rise in prison population, the decline of the crack epidemic, and finally the legalization of abortion in the early 19870s.

Although Levitt (2004) accounting can be convincing the overall assessment is still a matter of debate. Among the alternative explanations, Reyes (2007) estimates that 56% of the decline is due to a sharp decline in lead exposure that dramatically affected cohorts born after the Clean Air Act in the 1970s. In addition, Cook and MacDonald (2010) suggest that an increase in private actions regarding crime prevention and crime control policies could have played a central role, and more recently Wright et al. (2017) even argue that a decline in the use of cash can be an important additional factor. Overall, in spite of these remarkable efforts, the reasons why crime decline remains fairly uncertain. Phillip Cook summarizes a “remarkable conclusion” in this regard: “similar fundamentals of socioeconomic status are compatible with a homicide rate of both X and 10X, given relatively minor changes in circumstances” (Cook, 2008, p.7).

As opposed to a revisited version of the pessimism denounced by Becker in the late the 1960s, I argue that this remarkable conclusion can be connected with an important insight which is quite accepted in the field today. Observed crime rates is the outcome of a complex interactive system and can be modified by a multiplicity of channels rarely under a researchers control. Without a clear theoretical framework and a clean empirical strategy to address many of the possible endogenous reactions there is little we can learn about criminal behavior and how to reduce crime.

**Prisons as a crime-control policy tool**

In this section I offer a closer look at the particular role that prison has played on the crime decline. The massive expansion of incarceration is plausibly the most relevant social policy issue in the U.S. in the last fifty years. Incarceration rate remained pretty stable between 1930 and 1975, but it quadrupled between 1975 and 1995 (see Figure 1.2). Here rather than a philosophical discussion pertaining the role of prisons in a society, I consider a practical assessment of its effectiveness as a crime control policy tool.

As a first broad approximation, and given the evidence already discussed, it seems difficult to neglect that such an expansion in the use of incarceration has had no effect on the current levels of crime. By contrast, the question I would like to address here is how efficient the use of that particular tool has been, especially considering that this expansion has no parallel across most western democratic nations where crime has also declined.

One important thing to notice is that prison population does not represent a direct policy tool but rather of combination of factors, among others the institutional design of the
criminal justice system and the level of criminal activity (Nagin, 2013; Chalfin and McCrary, 2017). Thus an assessment of the evidence regarding prison effectiveness requires a complete examination of the potential factors driving this particular expansion. Raphael and Stoll (2013) model the variation in the stock of prison population as a Markov process based on empirical estimates of prison admissions, and expected time served by type of offense. A very useful feature of this model is the ability to create counterfactual scenarios of the steady-state prison population based on a given level of criminal activity and sentencing practices in place. They show that changes in the propensity to send convicted offenders to prison, and longer sentences for certain crimes account almost entirely for the increase in incarceration rate. In particular, among those two factors, they show that higher admissions rates play the more substantial role. In the same way, their simulations show very little evidence that this increase could have been driven by changes in the observed levels of criminal activity.
They complete the analysis showing evidence that rules out other possible candidates for the expansion such as the deinstitutionalization of the mentally ill population, a compositional change in demographics, and the exaggerated role of the crack-cocaine epidemic.

A direct consequence of expanding prison population by increasing the probability of admission and time served is a change in the composition of the prison population. In fact, as documented by Raphael and Stoll (2013) during the period of rapid expansion, the composition of inmate population shifted toward less serious offenders, many of them convicted for nonviolent drug crimes. As a result of this change we may expect that our previous estimates of the marginal effect of prison population size on crime may mask a fair amount of heterogeneity.

If we care about prison effectiveness in terms of crimes averted per prisoner, a compositional change will likely affect our assessment of prison as a crime-control policy tool. In particular, given the specific drivers of the expansion, it seems plausible to observe substantial diminishing returns to scale. In fact, R. Johnson and Raphael (2012) find a large reduction in the marginal effect of prisons on crime over the period 1991-2004 compared with 1978-1990 when prison population was rapidly expanding. Nagin (2013) also emphasizes this notion based on the idea of stochastic selectivity (Canela-Cacho, Blumstein, and J. Cohen, 1997) which accounts for the fact that relative to low-rate offenders high-rate offenders are more likely to be convicted and behind bars. In that sense, the question about the optimal scale of imprisonment becomes relevant, especially when prison population is driven by increasing disproportionally a large group of inmates who are much less risky to society.

In order to have a clear assessment of prison effectiveness as a crime-control policy tool a more fundamental distinction about the mechanisms is needed. Many estimates of the effect of prison population on crime do not distinguish between incapacitation and deterrence effects. Early works on deterrence highlight the threat of prison as an important crime control policy, and to some extent, this distinction should be taken in mind when analyzing every criminal justice policy, including the effect of police on crime. From a benefit-cost analysis perspective this distinction is crucial since the marginal costs of each of them are very different, especially when evaluating the appropriate scale of the policy. In that sense, a large piece of evidence shows that most of the effect of prisons on crime seems to be driven by incapacitating serious offenders while its role as deterring on-the-street offenders is very limited.

The incapacitation role of prisons corresponds to the mechanical consequence of putting someone behind bars and isolates him/her from the rest of the society. Prisons, often times, incapacitates the highest criminally active people. But as we have discussed, inmates may differ a lot in terms of their propensity to commit crime. Raphael and Stoll (2013) show that the likelihood of engaging in criminal activity tends to decline sharply with age, and particularly beyond the age of eighteen. This suggest a more specific channel of the diminishing returns of prisons. Considering the high costs of incarceration, it is not clear to what extent it is justifiable for other than retributive grounds to retain behind bars for a long time an inmate who imposes a very low cost to society in terms of crime risk.

One can plausibly argue that although the observe reduction in crime has not been driven
by incapacitating dangerous offenders that otherwise would be offending at a high rate, the new sentencing regime may have activated the role of prisons as a real threat which could have precisely prevented potential offenders from offending. In Becker’s model this may be considered in both the probability of apprehension \((p)\) as well as the cost of committing a crime (length of the sentence). The empirical methodological challenge here is how to disentangle deterrence from the incapacitation effect. A usual strategy has been leveraging natural experiments that increases the expected punishment (e.g. sanctions regime) without necessarily affecting the probability of conviction which arguably excludes a short-term incapacitation effect. A salient example is the implementation of California proposition 8 which imposed sentence enhancement for a selected group of crimes in 1982. Kessler and Levitt (1999) exploits this feature of this reform to isolate deterrence of sentencing enhancement from the incapacitation effect of prison. They propose a difference-in-difference strategy comparing the variation between crimes eligible and non-eligible for the variation in sentencing before and immediately after the introduction of the reform. They find that Proposition 8 reduce eligible crimes by 4 and 8 percent. Later on, these findings have been questioned by the choice of the period of time in the analysis (Webster, Doob, and Zimring, 2006), and the validity of the comparison group (Raphael, 2006).

The weak evidence of sentencing deterrence is reinforced by a large body of evidence. Raphael and Ludwig (2003) find no deterrent effect when examining the Project Exile in Richmond, Virginia that enhanced sentence for gun crimes. Other researchers have exploited the sentencing variation imposed by the majority age. In particular, they test whether there is a behavioral response in young people right when they turn the age of majority that usually expose them to a tougher sentence regime. Lee and McCrary (2017) use exact date of birth for a large sample of offenders in Florida and find little evidence of deterrence in spite of documenting a sizable discontinuity in the probability that a young offender is sentenced to prison when they turn eighteen. In a way, this finding is consistent with Hjalmarsson (2009) who assess degree to which change in knowledge corresponds to actual change in punishment severity. He shows that youth are aware of the objective change in sentencing, but the variation in perception is smaller than the actual change. In a way, this gap between objective and subjective perception in sentencing variation could explain why is hard to detect a significant effect. In a similar way, we should keep in mind an intrinsic limitation on this literature imposed by the use of arrest data. As noticed by Chalfin and McCrary (2017), if police are more likely to arrest adult offenders, using arrest data as a proxy for criminal behavior could attenuate the value of the deterrence coefficient.

Another source of exogenous variation that have motivated researchers to measure a deterrence effect of punishment is exploiting the variation in the use capital punishment across different state in the U.S. In a way, the difference between a death sentence and a sentence of life without parole offers an attractive setting to distinguish deterrence from a pure incapacitation effect. Although a first group of studies seem to offer persuading evidence of a positive effect in this case, more careful assessment of the evidence suggests that most of those studies have been plagued of identification issues and very sensible to the period studied (Donohue and Wolfers, 2006), especially when relying on aggregate crime rates using
time series (Nagin, 2013) and panel data (Chalfin, Haviland, and Raphael, 2013). There is a broad agreement that the evidence is at most mixed with a large number of studies implying no deterrent effect (Donohue and Wolfers, 2006).

Probably the most convincing evidence of a deterrence effect of prison sentencing is limited to situations where the policy is targeted to a restricted group of offenders who are also very aware of the sentencing laws. Helland and Tabarrok (2007) analyze the deterrence effect in a particular group of offenders induced by three strikes laws in California in 1994. After the passage of the reform they find that released offenders with two strikes are less likely to reoffend than released offenders with two trials for strikeable offenses but only one conviction for a strikeable offense. Importantly, they run a similar analysis in states without three-strikes laws and find no similar effect. In Italy, Drago, Galbiati, and Vertova (2009) find a similar result. They exploit a plausibly random variation in the sentence pending for offenders that were release as a result of the date of a large collective clemency bill passed in 2006. The intuition of the instrument is that the actual date of the pardon defined a pending sentence among released prisoners that could be exploited as an exogenous variation of prison sentence on their probability of reoffend. In particular, they estimate the relationship between residual sentence and recidivism holding constant original sentence, and find that among released prisoners one-month less time served in prison (which corresponds to one-more month in expected sentenced for future crimes) reduces the probability of recidivism by 0.16 p.p. A fundamental limitation of Drago, Galbiati, and Vertova (2009) is related to the distinction between general and specific deterrence. Specific deterrence refers to former offenders and the way that their own experience in prison may alter their behavior. In the case of Drago, Galbiati, and Vertova (2009), the definition of the instrument makes impossible to distinguish between these two effects due to the perfect negative correlation between time served and pending sentence for individuals convicted of an equal sentence. If the amount of time served in prison has a criminogenic effect as suggested by some researchers, offenders with higher pending sentence may offend less precisely because they spent less time in prison.

My general assessment of the evidence regarding prisons as a crime-control policy tool is at most very modest in terms of deterrence, and positive but with substantial diminishing returns to scale in the case of incapacitation. In a way, this finding can simply corresponds to a behavioral feature of the supply of offender’s function. A small or no deterrence may reflect the fact that potential offenders are myopic and have an intrinsic tendency to overweight immediate (lower) rewards relative to future (higher) costs. In other words, to the extent that offenders have a high discount rate, deterrence effects will be less likely (Chalfin and McCrary, 2017). In the specific case of severity of sanctions, Polinsky and Shavell (1999) and Polinsky and Shavell (2000) extend Becker’s model to show that if offender’s disutility of a prison terms increases less than proportionally with the length of the sentence, offenders will be more responsive to the certainty of punishment rather than the severity of punishment. In a similar way, Nagin and Pogarsky (2004) discuss how two specific forms of present-orientation behavior are associated with criminal behavior. The degree to which they accurately describe potential offenders, it could explain why deterrence is a very limited channel to reduce crime. They find that both discounting (tendency to deliberatively devalue the future) and poor
impulse control (failure to consider the future) predicts a range of problematic outcomes. In particular, they find that both are associated with property crimes, although high discounting was a stronger and more consistent predictor. By contrast, violent crime was only associated with poor impulse control and not high discounting.

Finally, the recent realignment process in California offers another empirical test of the modest effect of prison given the current high level of incarceration. A federal court forced the state to reduce the prison population which in practice suggests an interesting path of reducing prison without increasing the level of criminal activity. Starting in 2011, realignment reduced state prison incarceration rate from 426 to 348 prisoners per 100,000 residents, and the main variation was implemented during a short period of time (12% of the decline in the first month, and 82% within seven months). Lofstrom and Raphael (2016) find that this large reduction in incarceration causes no increase in violent crime while just a modest effect on property crime (auto thefts). In addition, Lofstrom and Raphael (2013) find that benefits in terms of prison expenditure savings outweigh the costs in terms of higher property crimes. Relative to the high cost of incarceration in California ($51,889 per inmate-year ) the savings outweigh the costs ($11,783) by far. This finding, again, confirms that prison, at least at the current level in California, is a very expensive crime-control policy tool. As we have discussed, and along with the careful Chalfin and McCrary (2017) review of the evidence of criminal deterrence, the fact that the elasticity of crime with respect to prison is generally modest relative to empirical police elasticities strongly supports the idea that moving resources away from prison to increase police manpower represents a more optimal crime control-policy.

1.3 Crime as a complex interactive system

An important takeaway of our selected overview of the literature is that crime is a complex and multifaceted phenomenon. In chapters two and three I present evidence that supports the relevance of incentives and situational factors on determining crime. I identify specific situations and policy-induced variations whose effects on criminal victimization are equivalent to enormous public policy interventions in terms of prosecution. In a way, all these findings attempt to diversify the portfolio of responses and the growing body of scientific understanding regarding criminal activity in urban areas.

How potential offenders and victims interact in the crime production function plays a central role in the following chapters. This is a feature of the criminal activity that has been emphasized very early in the economics of crime literature (Cook, 1979; Cook, 1986), but has hardly explicitly incorporated in most empirical studies. In this section I discuss the relevance of this framework as well as I leave some open questions for future research.
Understanding a crucial source of crime variation

In a way, a more explicit consideration of potential offenders-victims’ interactions can contribute to a better understanding of many empirical estimates in the economics of crime literature. This framework offers a natural validity check for an appropriate interpretation of a particular regression coefficient. Often times, researchers evaluate the effect of a policy that affects either the supply of criminals or their propensity to commit a crime on the overall level of criminal activity. The identification strategy of those empirical evaluations typically relies on the fact that a specific policy or shock was exogenous. In those cases, a critical condition for interpreting a regression coefficient as a supply-side reaction is that victim’s behavior remains constant or unaffected by the shock which exclusively altered the behavior of the former. Although in some situations this is not problematic, researchers have to be careful enough to clearly state under what conditions we should interpret a regression coefficient as the deterring effect on potential offenders or simply as the reduced-form effect on crime.

To illustrate that point let us consider a simple case. Imagine you want to evaluate the extent to which an increase in police presence deter criminals from offending. In order to avoid any endogenous responses associated with the criminal justice system you exploit a policy shock that suddenly increase police presence in a number of streets. Aside from issues regarding data collection and crime records, you have to be careful on interpreting the observed variation in criminal activity strictly as a potential offender’s reaction. Indeed, it does not seem to be unrealistic the possibility of finding a variation that is not statistically different to zero. More police may deter criminals from offending by increasing costs of committing a crime, but at the same time it may induce a reaction on potential victims; by increasing the perceived level of security in the environment victims can be induced to adopt less precautionary policies (riskier behavior in terms of victimization, or simply spending their resources away from precautionary measures to other activities). As a result, you may find no significant variation in criminal activity as both responses offset to each other. If victims reaction is similar or larger than offender’s response we may wrongly conclude that police presence did not deter criminals from offending.

A concrete application in that regard is described in chapter three: Crime-Time: The Effect of Ambient Light on Criminal Activity. We present robust evidence of how ambient light affects criminal activity in the urban space. The main finding is that more ambient light reduces crime significantly whereas less light increases the amount of property and robbery crimes. Since we focus our analysis for a particular period of the day and over a short period of the year, we argue that the variation in ambient light is exogenous to many other activities that could also mediate the relationship between them. From a policy perspective this is a very important finding if we care about the level of criminal activity in the urban space and how to reduce it. From a social science standpoint, we may also care about the specific behavioral component of that finding (e.g. the extent to which ambient light deter criminals from offending). This is a question about the mechanisms underlying that particular finding. In this case, again, our general framework where potential offender
and victims interact provide an important insight.

Since people are aware of the Daylight-Saving Time policy it is hard to believe that the variation in ambient light is unexpected which may raise a concern regarding the extent to which the observed variation is driven by a behavioral response of potential victims. In fact, we can imagine many possible endogenous reactions from the victim’s side that could potentially affect the crime production function. Ideally, we would like to fully describe people’s behavior but even a large set of controls would be insufficient to rule out all possible unobservable factors. Acknowledging that limitation we propose to run a reasonable test that shed some light on that regard. If potential victims simultaneously alter their time-commuting pattern to the variation in ambient light induced by DST, we could empirically test such a reaction. We use Metro ridership data at the same frequency level, and for the same period of analysis, and find no significant variation in the number of passengers riding Metro at any hour of the day. Although Metro ridership represents a broad measure of victim’s behavior, this finding suggests that at least the major portion of the crime variation is unlikely to be driven by an endogenous reaction in the commuting pattern which represents a key indicator of victim’s behavior. Certainly, that could not rule out other possible endogenous responses (people may stick with their calendars but actively change other precaution measures while commuting) but at least is indicative that a strong endogenous reaction from the victim’s side is unlikely to fully explain the large observed variation that we find.

A more complex social welfare framework

There is a second reason that justifies a more explicit consideration of victim’s behavior in crime empirical studies. By modifying their behavior victims can reduce their victimization risk, but also can potentially affect the level of violence offenders exhibit against them when victimized. This is a specific finding of the second chapter when I incorporate offender’s weapon’s choice as a proxy of the level of violence exhibited by them. I show that the lethality of the weapon’s choice is responsive to the expected level of resistance opposed by victims. In other words, potential offenders react not only in terms of their propensity to offend but in the way they choose to threaten a victim. In particular, I show that conditioning in the probability of being victimized the level of violence exhibited by an offender is greater when victims are more likely to protect their goods. The rationale for that specific response comes from the fact that the benefit from using a firearm (relative to using a less lethal weapon) is greater when victims are more likely to resist an attack. In chapter two I also show strong empirical support for this particular theoretical prediction.

The level of violence exhibited within a certain crime-category represents a relevant dimension that is rarely incorporated in welfare analysis. However, it is clear that it can dramatically affect people’s wellbeing. To some degree, this finding suggests the existence of a tradeoff victims could potentially face between a certain risk of victimization and the level violence they are exposed to in a given encounter. Future research should explore how much a decrease in victimization risk people would be willing to trade in exchange for an increase in the level of violence they are exposed when victimized. This could be an especially pressing
consideration on evaluating the benefits of a policy that harden a particular target but fails to reduce the level of victimization.

**Public versus private efforts in crime prevention and control**

The crime-returns of public and private efforts can differ substantially, and especially when we know that private precaution measures which not necessarily reduce crime at any margin. In a way, there are many situations where private and public spending may compete or complement each other in the provision of crime prevention and protection. Therefore, a key consideration towards finding a diverse portfolio of policy and actions that account for the complexity of crime, is the amount of crime prevention that should be allocated through either public or private efforts.

This issue is closely connected to a central question in fiscal policy design where the degree of substitution between public and private spending predicts the extent to which an increase in public spending crowd-out the amount of private provision of a public good. In the case of crime prevention and control provision, individual victim’s incentives can differ a lot from public’s aggregate preferences (Clotfelter, 1978; Shavell, 1991). In theory, what matters is how well private incentives coincide with social costs (Cook and MacDonald, 2010, p.338). This is something very difficult to assess empirically and have important equity considerations since private actions can either deter or displace crime.

Based on those considerations, we can discuss a final aspect regarding potential victim’s behavior and the role they have played in the dramatic crime reduction observed in the U.S in the last 25 years. This is a much more speculative point but may open an interesting avenue for future empirical research questions. If it is true that private precaution measures played a key role in the great American crime decline, as suggested by (Cook and MacDonald, 2010), we can ask the extent to which such a way of preventing and controlling crime could have been achieved more efficiently achieved through public spending. This could be a particularly pressing issue, especially if the kind of investment private agents pursued actually displaced some portion of the criminal activity to places where other private agents were less likely to invest in private protection measures.

Alternatively, considering that protection against the risk of victimization is costly, we can think that precisely as a result of the decline in crime, victims could have been gradually adapting their behavior reducing their own private protection measures. Although it is clear that those (private) savings represent a benefit of the crime reduction, it is less clear how much they have attenuated the effectiveness of public investment devoted to prevent and controlling crime. The extent to which private individuals are substituting their crime prevention efforts away and how much public spending crowds-out those efforts is definitely a challenging empirical question but an important one for those who care about public policy, how to create public value and improve the overall quality of life.
Chapter 2

How Potential Offenders and Victims Interact: A Case-Study from a Public Transportation Reform

This paper models crime rates as a function of the interaction between potential offenders and victims. I present a simple model of these strategic interactions, and empirically test its basic predictions taking advantages of a reform to the public transport sector in Santiago, Chile (Transantiago). First, I discuss the extent to which a decline in the use of cash for economic transactions affects crime. Due to the highly liquid nature of cash, we may expect that places where a large amount of economic transactions are made in cash may have more crime opportunities. Under different identification strategies, I find a large decrease in cash-related robberies coinciding with the replacement of cash fares with a cashless card. In addition, I study how victim’s behavior affect the level and nature of crime. I exploit a particular feature of Transantiago’s transition period where compensation structure of bus drivers was required to change from being paid from a portion of revenue to receiving fixed salaries. For this period, I find a large increase in crime along with a proportional decrease in violence associated with the change in driver compensation structure. This particular response can be described under a moral hazard framework between bus owners (principal) and drivers (agent) which may have induced a large increase of criminal opportunities.
2.1 Introduction

This chapter attempts to understand the role of potential offenders and victims in determining overall crime levels. Most empirical evaluations in the economics of crime literature focus on the extent to which a particular policy deters or incapacitates potential offenders. Very little attention is paid to the strategic interaction between potential offenders and victims, a factor that may be an important determinant of the overall level of criminal activity. This issue was raised many years ago by Cook (1979) yet few empirical studies have satisfactorily explored this relationship. Indeed, Cook, Machin, et al. (2013) refer to this endogenous bidirectional “loop” between victimization risk and crime prevention efforts as “largely neglected in the economics literature” (Cook, Machin, et al., 2013, p.10) 1. Under this framework it is clear that observed crime rates are not only the result of offenders actions, but also the interaction between their choices and the choices of potential victims. 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 the role of victims and potential offender in criminal activity, 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 onboard safes into which fares were dropped has been recognized as a classic crime-prevention measure (Smith and R. V. Clarke, 2000). Exact-change fare collection systems or alternative efforts to harden the target are still rare in developing countries where the public transport sector is lightly regulated and mostly operated by informal and often privately-owned transit operators. For instance, in Santiago, the capital and by far the most populous city in Chile, fare payment using cash was the universal norm through 2007.

I develop a simple model of the behavior of potential offenders and victims to lay out possible consequences for aggregate crime rates resulting from two exogenous shocks: a change in the incentives for victims to harden the target and a change in the expected value and liquidity of the take from a specific form of crime. I then empirically test the main predictions of the model taking advantages of a sequential set of reforms implemented under the guise of the Transantiago public transit reform program commencing in 2005.

This paper make several theoretical and empirical contributions to the economics of crime literature. First, I discuss the extent to which a decline in cash transactions in everyday economic transactions impacts crime. Due to its high liquidity and largely untraceable nature, cash represents a very attractive criminal opportunity. Thus, holding everything else constant, we may expect lower levels of crimes in those contexts where economic transactions are less likely to involve cash. In a related case study, Wright et al. (2014) analyze the effect

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1In a similar vein, Nagin, Solow, and Lum (2015) has recently referred to Cook’s (1979) paper as a “valuable and underappreciated work”. (Nagin, Solow, and Lum, 2015, p.79)
CHAPTER 2. HOW POTENTIAL OFFENDERS AND VICTIMS INTERACT

of cash on street crime and based on their empirical findings suggest that a reduction in the use of cash in everyday economic transactions can be considered as an alternative hypothesis explaining the great American crime decline (Zimring (2006); Levitt (2004)). In this case, I empirically estimate this relationship, by taking advantages of the replacement of the cash-payment system by a smart contactless debit card in all buses during the implementation of Transantiago. Employing multiple identification strategies, I find robust evidence of a substantial reductions in robberies reported on buses coinciding with the move to a cashless system.

In addition, I analyze how a change in the incentives for a victim to resist impacts the level and nature of crime. Here, I focus on a transition period of Transantiago preceding the implementation of the debit card, 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 route planning and rolling out the debit technology. During the interim period, bus drivers’ compensation shifted from 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 their operators (principal). Under this new scenario, we suggest that bus drivers were less likely to adopt costly measures to protect the money collected on each ride since their salaries were no longer in danger. Moreover, I investigate how this new salary policy may have also affected the level of violence that is incidental to robberies of bus drivers. Specifically, I model how the incentive for robbers to threaten with greater lethality changes with the change in driver compensation structure, operationalized as the choice between using a gun or knife in the robbery. The model predicts that the lesser incentives for drivers to protect the fair box reduce the relative returns to using a more lethal weapon. I empirically test these two predictions, and I find a dramatic increase in robberies along with a substantial reduction in the proportion of robberies involving a firearm incidents when victim’s incentives to resist an attack decreased.

2.2 Criminal Opportunity Theory

The economics of crime literature has long emphasized the role of offenders and the extent to which specific mechanisms such as exogenous variation in police staffing levels (Levitt (2002); Di Tella and Schargrodsky (2004); Draca, Machin, and Witt (2011); Chalfin and McCrary (2013)), incapacitation (Levitt (1996); Buonanno and Raphael (2013)) or sentencing policies may deter or incapacitate. But victim’s behavior can plausibly affect the level and nature of criminal activity by adopting multiple actions; they 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 purchases goods and services that either reduce the likelihood of being victimized
or minimize the costs associated with a victimization \(^2\). The role of victims has not been necessarily unnoticed, but to date has been relatively under studied \(^3\). 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.

In the economics of crime literature, an important theoretical contribution regarding the role of victims is (Cook, 1979; Cook, 1986). 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 to crime 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 they perceive. In other words, the degree to which potential victims undertake self-protection measures depends on the perceived risk and costs of victimization.

The relevance of victims in the aggregate measures of criminal activity has been recently emphasized by Cook, Machin, et al. (2013). They highlight that despite the growing body of crime research by economists, empirical research on this issue is still relatively underdeveloped. Among the difficulties, they mention the fact that observed crime rates are the outcome of a complex interactive system where aggregation of individual choices may lead to surprising results, especially if we do not take into account how different agents interact in this particular market. In particular, they identify three feedback loops. First, they mention the relationship between the criminal justice system and crime rates: “the capacity of the criminal justice system to control may be diluted by an exogenous increase in crime rates, which then causes a reduction in the likelihood or severity of punishment resulting in further increases in crime” (Cook, Machin, et al., 2013, p.10). In a similar way, crime rates are endogenously related to the political salience of crime; variation in crime rates may affect the resources allocated to the criminal justice system with subsequent effects on the crime rate. Finally, victim’s behavior represents a third loop since it is endogenously related to the level of crime as we describe earlier. While Cook, Machin, et al. (2013) emphasize that the first two loops have been incorporated by employing different econometric specifications, a comparable effort to account for the endogeneity and impacts of victim’s behavior has been relatively under-developed.

Among the empirical studies that have focused on victim’s behavior and how they modify

\(^2\)Freeman (1999) guest that around 0.6 % of US GDP is spent on private crime prevention (taking a taxi instead of walking for some particular activities or locating a business in the suburbs instead of a central 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 in this regard are: Clotfelter (1977) and Shavell (1991).
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. They analyze the particular case of the business improvement districts (BIDs) in Los Angeles which are non-profit organizations created by neighborhoods property owners with the purpose of providing some local public goods, including public safety among them. They show that social benefits of BID expenditures on security largely exceed their private expenditures (20 times). In addition, they find no evidence of displacement and an important decrease in arrests which is an extra public benefit that led to subsequent savings in the criminal justice system.

In a similar way, Vollaard and Van Ours (2011) have shown that victims can also alter the set of criminal opportunities by hardening an attractive target. They evaluate a large-scale government intervention in the Netherlands that affects home safety. They take advantages of a regulatory change that required new-built homes to have burglary-proof windows and doors, and find a significant reduction in burglary risk in new homes. Interestingly, they find no displacement to older homes or other property crimes such as car or bicycle thefts. Again, in this case, they highlight that social benefits of this particular regulation are likely to exceed the social costs.

Other empirical studies have emphasized situations where victims alter offender’s incentives by modifying the nature of the target. We can expect that a shock to the liquidity of the loot can deter criminals from stealing a particular object. In that sense, changes in cash circulation\(^4\), as well as the incorporation of tracking devices in cell phones are commonly referred as practical ways to deter crime. A well-known experience are two empirical evaluations of the effect of Lojack in criminal activity. Lojack is a hidden radio-transmitter device which is highly effective for recovering a stolen vehicle, thereby reducing the reward from stealing. Ayres and Levitt (1998) evaluate the deterrent effect of this technological innovation and exploit the differential timing of arrival across US cities. They find a large reduction in auto-thefts associated with the availability of Lojack. Given this particular setting where the installation of the device was unobservable for the offenders, they interpret this result as a general deterrence effect. They also find no evidence of displacement or substitution across other crime-categories, except for older vehicles which were precisely less likely to have LoJack installed.

More recently, Gonzalez-Navarro (2013) exploits a slightly different setting where only new Ford car models explicitly incorporate Lojack devices in a set of Mexican states. He finds a large (specific) deterrent effect in Lojack-equipped vehicles but, as opposed to Ayres and Levitt (1998), he also finds a crime increase in unprotected Lojack models in non-Lojack states. Gonzalez-Navarro (2013) interprets this finding as evidence large geographical displacement, or alternatively stated, a negative externality. Importantly, this evidence of a negative externality in is not inconsistent with the positive externality documented by Ayres

\(^4\)The relationship between cash and criminal incentives exceeds the direct reward associated from stealing money. In this regard, 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.
and Levitt (1998) since in this case the presence of the device was presumably observable (Ford car models in some states) to potential offenders.

Although empirical evaluations of Lojack have been motivated by the study of how victim precaution may affect crime, both cases clearly refer to a situation where the very nature of the stolen good is modified. No further victims behavioral responses are considered in either situation. It is important to recognize that this omission, however, rather than threatening their findings may strengthen them. In the case of Ayres and Levitt (1998), the increase in safety may have presumably encouraged more careless behavior in all potential victims which may have led to an increase in crime, however the authors find exactly the opposite. Consistently, plausible adaptive responses in Gonzalez-Navarro (2013), if any, may have led him to understate the displacement effect.

Finally, a more closely related study in terms of the effect of reducing cash transaction in criminal activity is Wright et al. (2014). Specifically, they analyze the effect of cash on street crime exploiting the variation in the timing of the implementation of Electronic Benefit Transfer program (EBT) across Missouri counties. They found that overall crime decreased by 10% as a result of the implementation of EBT system. Considering the magnitude of this estimate, they suggest that a decrease in the use of case in everyday transactions could be incorporated as an alternative hypothesis of the great American crime decline ((Zimring, 2006); (Levitt, 2004)).

There is a perhaps more developed incorporation of victim behavior and criminal opportunities in the situational crime prevention literature pioneered by Ronald V. Clarke. Clarke and his collaborators have documented a set of different experiences where the criminal activity is affected by variations in the situational factors surrounding crime rather than exclusively focusing on offender’s motivations. Thus, he focuses on the criminal event rather than only the factors influencing individual decisions to be involved in (or desist from) criminal behavior. Indeed, this approach emphasizes that a realized criminal act cannot be fully described by an individual offender’s motivation. Clarke argues that beyond a willing offender, an actual victimization requires a vulnerable target and an appropriate opportunity. In short, the main elements of this theory incorporate both a description of the nature and distribution of criminal opportunities as well as an accounting of offender decision-making.

Clarke presents theoretical and practical arguments for the relevance of situational factors in determining crime rates that we can easily extend to the role of the behavior of potential victims and the available set of criminal opportunities.

Clarke takes issue with traditional rational choice models of crime that strongly empha-

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5 As opposed to the classical rational choice approach (Becker, 1968), Clarke highlights the opportunistic and reckless nature of a significant portion of crimes (R. V. Clarke, 1995). According to Smith and R. V. Clarke (2000) this approach brings together different branches of the criminology literature such as routine activity theories (L. E. Cohen and Felson, 1979), rational choice perspective (R. V. Clarke and Cornish, 1985), and the environmental criminology (P. J. Brantingham, P. L. Brantingham, et al., 1981).

6 People choosing to take advantage of naturally arising opportunities or as deliberating creating opportunities; rather than “passive actors” compelled to behave criminally by deeply rooted causes (R. V. Clarke, 1983, p.231)
size the idea of a rational utility-maximizing agent who carefully calculates the costs and benefits of every available criminal opportunity. He states that traditional rational choice models “does not fit the opportunistic and reckless nature of much crime” (R. V. Clarke, 1995). Although, he acknowledges that criminal behavior involves an important degree of rationality (choice), he argues that criminal behavior is more appropriately modelled as rudimentary, and constrained or bounded by the circumstances. In addition, the consideration of situational factors offers a chance to incorporate into theory some deviant behaviors such as impulsiveness, peer influence, and other such factors that are difficult to incorporate into a rational choice framework. Clarke argues for an emphasis on criminal motivation rather than long-term disposition as providing a clearer explanation of why crime occurs at particular times and places.

The explicit incorporation of situational factors has important consequences from a practical point of view. Relative to analyses focus on the deep causes (social roots) of crime, and along with rational choice theory, it offers a practical scope for action in terms of actual policies that can be implemented to prevent crime. Indeed, Clarke refers to a dispositional bias in the criminological theory that suggests that nothing works in crime control policies. In addition, from a cost-benefit perspective, addressing the circumstances that are conducive to or encouraging of deviant behavior can be much more efficient that trying to modify deep social causes of crime.

Perhaps, one of the most famous experiences that illustrates the appropriateness of this approach to study crime is the unintended effect on crime of mandatory helmet laws. Mayhew, R. V. Clarke, and Elliott (1989) find a large decrease in motorcycle thefts after the passage of the law. This experience also highlights the opportunistic nature of crime since no evidence of displacement to other similar crime activities (auto or bicycle thefts) was found. According to the authors, after the passage of the law only few potential thieves had a helmet with them at the opportune time and place, thus the high risk of being stopped by the police acted as a strong deterrent mechanism.

Finally, regarding the particular case I analyze in this paper, Smith and R. V. Clarke (2000) present a description of why public transport is an interesting case for analyzing how environmental factors affect crime. Although they attempt to illustrate the relevance of situational factors on criminal activity, they mention several cases where victims can certainly affect the nature and level of crime. They distinguish between crimes facilitated by overcrowding and those facilitated by lack of supervision as two important choice-structuring properties of public transport. Interestingly, they 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 D.C. and then in New York in May, 1968. Chaiken, Lawless, and Stevenson
(1974) highlight that after the introduction of exact fare change, robberies of drivers dropped dramatically in buses, and interestingly, they also report a subsequent increase in the subway system.

In addition to the presence (absence) of cash in a particular environment such as the case of public transport sector, the situational crime prevention approach has also emphasized the sentinel role of particular agents in determining the overall crime level. For instance, Clarke (1983) shows different cases where residents and employees have affected vandalism and other illegal behavior. In particular, he refers to the case of vandalism on double-deck buses (Mayhew, R. V. Clarke, and Elliott, 1989) where a lower number of incidents was found in buses operated by a driver with the assistance of a conductor, relative to those that where were operated by a driver alone. Interestingly, the differences were found only in seats located at the upper deck, and no differences were found for seats located at the lower deck.

Below, I describe the set of reforms to the public transport sector implemented under the banner of Transantiago. I then present a simple model that describe how these reforms altered the incentives faced by victims and offenders, and how these changes impacted overall crime rates. In the empirical section, I test these predictions exploiting the staggered timing of the implementation of the various elements of these reforms.

2.3 The Implementation of Transantiago

In the early 2000s, on-the-ground public transport in 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, driver’s working conditions were significantly modified. Most importantly for our purposes, their compensation structure changes from earning a proportion of daily fare revenues to a fixed amount defined independently of the number of passengers on each particular ride.

In this section, I describe the implementation of Transantiago and the main motivations behind this policy. This was a highly ambitious plan and after the first months of fully implementation was exposed to severe public criticism due to many issues associated with the design and actual implementation of the policy. I will pay specific attention to the aspects of the reform that plausibly affected the criminal activity reported in buses, especially regarding robbery incidents.

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7This report mainly focuses on the impact of police activity on crime in the New York City Subway system. Smith and R. V. Clarke (2000) also mention a Stanford Research Institute study (1970) that report similar results in a review of the effect of exact fare systems in 18 other cities.

CHAPTER 2. HOW POTENTIAL OFFENDERS AND VICTIMS INTERACT

Pre-reform system

The origins of the previous transport system can be traced back to the Chilean dictatorship of the early 1980s when the government privatized and deregulated the bus system. While new regulations of bus transit were introduced during the 1990s, the industry 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 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. A notorious feature of this lack of integration was the payment system. Figure 2.1 shows a typical bus drivers space which illustrates the old payment mechanism. Passengers paid their fare tickets by 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 their tickets. In addition, drivers were responsible for protecting the money collected in the so-called “Peceras” (Spanish word for fish-tank), a responsibility that bore directly on their pay. Operators paid bus drivers’ salaries according to the number of passenger’s 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 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 carry on average 60km before they could do the accounting balance in a safe place. “Peceras” were implemented as open boxes which allowed bus drivers to constantly sort the cash they were receiving, and give cashback to their passengers. Often, they decided to carry sticks or some non-firearm weapon as a personal safety measure against an eventual assault 9.

The particular working condition of bus drivers under this system and its effects on the overall performance of the system has been investigated by others. R. M. Johnson, Reiley, and Muñoz (2015) analyze how driver compensation affects bus system performance in Chile during the previous public transport system in 2004. They compare differences between a first group composed by two companies (332 buses) where drivers were paid fixed salaries, and a sample of companies from the rest of the system (7,700 buses) where drivers were paid based on passenger transported. They find that relative to fixed-wage system, the per-passenger system through a very proactive behavior leads to 13% shorter passenger wait times 10. According to R. M. Johnson, Reiley, and Muñoz (2015) this advantage comes from

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9Gallagher 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, Eastal and Wilson (1991) reports the use of weapon as one of the self-protection measures implemented by taxicab drivers.

10They described the particular phenomenon of the “war of fare” which comes from drivers strategy to maximize fare revenues by reducing bunching of buses. Interestingly, they argue that this reduced bunching of buses under a per-passenger compensation mechanism came along with the creation of informal entrepreneurs (called “sapos”) who were standing up in specific corners informing drivers about the locations of other buses in exchange of a small fee paid by drivers. This information was crucial for bus drivers
Figure 2.1: Bus driver’ space inside a bus during pre-reform and transition period

Notes: At the right hand side of the bus driver was commonly located the cash-payment box. The so-called "peceras" allowed bus drivers to collect cash, and paying each passenger their cashback with the specific fare ticket accordingly. Source: http://mqltv.com/10-cosas-recordaras-viajaste-una-micro-amarilla/ extracted on March 19th, 2017

a higher level of motivation of bus drivers who are paid on a per-passenger basis\textsuperscript{11}. However, this advantage in terms of system performance is also associated with a critical drawback, namely more aggressive driving\textsuperscript{12}. R. M. Johnson, Reiley, and Muñoz (2015) show that the per-passenger system also lead to 67% more accidents per kilometer driven.

While driver working conditions were certainly a motivation, the reform effort was driven who chose to drive somewhat faster or slower in order to create more profitable spacing (R. M. Johnson, Reiley, and Muñoz, 2015, p.1401).

\textsuperscript{11}Indeed, they notice sharp differences in the behavior of drivers. Drivers paid per passenger were excited to get back on the road. They took quick bathroom breaks, quick meal breaks, and were always ready to depart when the inspector (who regulates departure times) called them. At the depots of fixed-wage bus companies, drivers were often not ready when the inspector called them. They took longer meal breaks, spent more time socializing, and often use bathroom and other excuses to delay leaving (R. M. Johnson, Reiley, and Muñoz, 2015, p.1401)

\textsuperscript{12}Muñoz, Ortúzar, and Gschwender (2009) also identify two particular behavioral responses associated with this compensation mechanism: bus drivers used to skip stops with few passengers and refusing schoolchildren who paid a third of an adult fare.
CHAPTER 2. HOW POTENTIAL OFFENDERS AND VICTIMS INTERACT

in large part by the need to modernize the system in a broad sense. The two main identified problems were an 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 passengers’ costs. Therefore, in order to get the most of the demand, operators tended to privilege routes that minimized passengers transfers in the system. As a result, and given the urban structure of the city, most buses passed through downtown and connected two points of the city’s periphery with 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% of bus services circulated through the main six avenues of the city which clearly accentuated the problems of traffic congestion and air pollution.

On the other hand, 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 due to the fact that they separately attempted to collect the highest number of passengers on each ride.

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 (reducing street congestion, reducing travel and waiting time, and car accidents; Díaz, Gómez-Lobo, and Velasco, 2004). In addition, the government required the system to be environmentally, socially and economically sustainable. The environmental goal was particularly important given high levels of air pollution in Santiago at the time. The government defined the aspired-to economics sustainability of Transantiago as a system that “would be subsidy-free and charge and 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
New organization of the industry and new routes: It defined 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 in 15 zones and all buses were provided by 15 different operators (zones of bus services). The entire industry structure was franchised through an international call for tenders in 2004. Each of these “service areas” was defined to be serviced by a single company that won out in the bidding process. In addition, to minimizing the possibility of on-the-street competition, new companies were required by law to pay fixed salaries to bus drivers.

A Modern bus fleet: Companies were required to put new buses into service gradually. As opposed to the old buses, the new vehicles are equipped to service disabled rider and may accommodate more passengers. Also, since the system was designed to be more efficient in terms of ridership, the original design contemplated the operation of 5,000 buses which modified the number of buses circulating that were 7,700 prior to the reform.

New payment system: In order to make system integration effective and reduce on-the-street competition, the system required the implementation of a new payment system that allow transfers at low or no cost. The defined mechanism was a debit contactless card (Tarjeta BIP) and all buses and Metro were equipped with the machinery necessary to read the information on these cards. BIP cards are charged with cash at special locations including all Metro stations and other public spaces (typically local stores).

Importantly, the government established two different periods for the implementation of this new transportation plan. First, a transition period started in October 2005 where new companies started to familiarize themselves with the system and were assigned to run more services using old routes. In particular, five of the 15 new companies switched immediately to fixed-wage drivers’ compensation (R. M. Johnson, Reiley, and Muñoz, 2015). In terms of system operation, the transition period meant no major changes for passengers except for the gradual entrance 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 45.3km to 83.8 km in December 2006.

\[^{13}\text{These three key elements were already present in the former proposal developed in the PTUS plan which was relaunched as a proper policy during president Lagos administration in 2002 (Ureta, 2015)}\]

\[^{14}\text{Prior to the implementation of Transantiago, Metro had already implemented a non-cash payment system, so the reform did not affect its payment system. However, since Metro was fully integrated to the transport system, after the reform passengers were allowed to transfer from buses to Metro for a low-cost fare.}\]
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For the second period, changes in the public transport system were substantially more relevant. The government had previously decided that the core elements of the system (New routes and fare integration between all buses and Metro) should be all implemented in a single day. Although, originally proposed to be in October, 2005, the definitive initial date was postponed to February 10th, 2007 when the final expansion of Metro’s network was already available and operators would have a significant portion of new buses available. The reform implementation delay to 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 started to be exclusively operated by the new 15 firms which were required to pay fixed salaries to their drivers. 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 in the system. People were required to charge their cards in advance. Furthermore, by using this card passengers were allowed to transfer from any bus to Metro or to another bus at no or low cost.

Given the main events associated with the implementation of Transantiago we can define two main periods of analysis. The pre-reform period covers the first day for which crime data is available (January 1st, 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 riding along the old routes. The cash-payment system was still in place during this period but new firms are operating within the given 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 identified in the system. Finally, the post-period sharply begins on February 10th, 2007 when the full integration between buses started and the cash-payment system was replaced by the BIP card in buses. Figure 2.2 illustrated the timeline of events.

2.4 Analytical Framework: A Model for Criminal Activity

In this section, I lay out the features of a simple model of offender-victims interactions 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. We consider two basic agents: potential offenders and bus drivers. Both agents interact with each other, respectively, maximizing the gains or minimizing the loses of an eventual attack. We present the simplest version of the model, and also incorporate in the appendix two additional specifications: (1) allowing for a strategic interaction between agents with an endogenous model in the probability of attack, and (2) Incorporating different levels of violence associated with the weapon used by the offender.
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 collected in the fare collection boxes when attacked. They take into account the expected loses \( (G_D) \), the costs of adopting a high resistance strategy \( (c_i) \) which is idiosyncratic of each driver \( i \), and the probability that the offender is successful in the attack as a function of the resistance \( (P_H, P_L) \). We 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 loses when exhibiting with a high-level of resistance when attacked.

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

\[
U_i = \begin{cases} 
U_{H,i} = -P_HG_D - c_i, & \text{if } r = H \\
U_{L,i} = -P_LG_D, & \text{if } r = L 
\end{cases}
\] (2.1)

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

$$H \equiv \Pr[U_H > U_L] = \Pr[-P_HG_D - c_i > -P_LG_D] = \Omega[(P_L - P_H)G_D] \quad (2.2)$$

Based on (2.2), bus driver’s decision rule stated (2.1) has a clear interpretation: likelihood of adopting a high-resistance strategy depends directly on the expected loses ($G_D$), and the differential return of the high-resistance strategy ($P_L - P_H$).

**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 opposed by the driver. Assuming that $c_i$ is unobserved for a particular offender, but they know its distribution $d\Omega(c)$ for a particular period of time, $P_S$ can be written as: $P_S = H P_H + (1 - H)P_L$, where $H$ represents drivers likelihood of offering a high resistance-level. 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:

$$U_i = \begin{cases} U_{A,i} = P_S G - S, & \text{if Attack} \\ U_{NA,i} = b_i, & \text{if Don’t attack} \end{cases} \quad (2.3)$$

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

$$P_A \equiv \Pr[U_A > U_{NA}] = \Pr[b_i < P_S G - S] = \Psi[P_S G - S] \quad (2.4)$$

The expression in (2.4) 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 potential offenders propensity to attack a bus driver.

**Main Predictions**

I discuss the theoretical predictions in terms of criminal activity associated with two exogenous changes that modified agent’s incentives. 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 to bus drivers during a period of time were the fare was still paid exclusively by cash affected the level of crime observed during the transition period. In a sense, this reform decoupled potential offender’s expected gains from drivers loses. In other words, the transition period is represented by a shock that affected driver’s propensity to protect the cash collected on each ride. We also discuss the effect on crime incidents of the implementation of the cashless debit card as the exclusive payment method starting on Feb, 2007. In a way, this policy directly affected offender’s expected reward. Finally, in section 2.7, I discuss how the introduction of fixed salary policy also affected the level of violence adopted by offenders given the differential variation on driver’s propensity to resist an attack.

Fixed salary policy lead to an increase in crime

The transition period decoupled gains from losses in the model. Offender’s expected reward remain 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, $d$ fall below one (or may even have fallen to zero). Hence, the probability of exhibiting high resistance during these two periods can be written as

$$H \equiv H(t = pre) = \Omega[(P_L - P_H)G] = \Omega[G(P_L - P_H)] \quad (2.5)$$

whereas in the transition period,

$$H' \equiv H(t = tra) = \Omega[(P_L - P_H)G_D] = \Omega[G(P_L - P_H) \times d] \quad (2.6)$$

Since $d < 1$, it is clear that $H > H'$, driver’s level of resistance unambiguously declined in the transition period. Similarly, we can show that $P_S \equiv P_{S,pre} < P_{S,transition} \equiv P'_{S,transition}$, offenders are more likely to success during the transition period. 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:

$$P_A \equiv \Psi[P_SG - S] < \Psi[P'_SG - S] \equiv P'_A \quad (2.7)$$

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

Elimination of cash payment system reduces criminal incidents

In the post-reform period, a new payment method was introduced eliminating the possibility of paying with cash inside buses. In our model, this policy drastically reduces the expected

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15Detailed proof is available in the appendix section.
reward from attacking a bus driver. I model that by introducing a subscript in offender’s expected reward in the post-reform period. Formally, I assume that $G_o < G$. A clear prediction in terms of criminal incidents depends on the extent to which the reduction on the expected reward offsets an increase in offender’s probability of success. Again, considering the pre-period as a benchmark, expected rewards are substantially lower: $G_o << G$; but according to our model, due to the reduction on the expected loses driver’s propensity to resist can be lower as well, which subsequently drives offender’s probability of being success to be larger: $P_S \equiv P_S(t = pre) > P_S(t = post) \equiv P'_S$. Thus, based on the offender’s propensity to attack, a general condition for a reduction in overall criminal activity, relative to the pre-reform period, is: $P'_S G_o < P_S G$.

Interestingly, we know that during the post-reform period cash transactions were eradicated from buses. Thus, we can argue that the variation of the expected reward is much larger than the variation in offender’s probability of being success. Indeed, we can think that a more realistic approach is assuming that $G_o$ is some value close to zero\(^{16}\). In that case, the implementation of the cashless payment system should have led to almost eradicating cash-related incidents reported in buses. In the empirical section I discuss the extent to which this particular result holds.

### 2.5 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. 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 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 where no policy variation was in place as the reference category. Each of the identification strategies I propose rest on alternative identifying assumptions. While each individually can be limited, I believe that they collectively complement one another and that in conjunction, point to a causal effect of

\(^{16}\)The rationale for that prediction can be described as follows: 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 $G_o$ as low as eliminating incentives 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 any other potential victim in the urban space (opportunity cost $B$).
the reforms on crime rates. The main assumption is that the policy changes are exogenous to crime trends and thus that the differences in crime can be attributed to the policies in place during each period. This assumption is particularly restrictive in the case of time series, but certainly less restrictive for the case of the difference-in-differences and triple differences estimates.

In this section, I first describe the data used in the study. Then, I describe the three different identification strategies proposed, and discuss how they complement to each other under this particular setting. In section 2.6, I present the basic estimates associated with each alternative approach.

Data Description

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

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

I collapse the data to the weekly level\textsuperscript{17}. Using all crimes reported to police during the three main periods of our analysis, I create a panel of different crime incidents reported in specific places during 314 weeks. Table 2.1 compares the weekly average level for robberies reported in buses and public spaces. Robberies in 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 larger than the United States (\(\approx 100\) robberies per 100,000 people in 2014)\textsuperscript{18}. The robbery rate in 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 2.1 also shows how robberies in buses changed over time with a large increase during the transition period and a considerable decrease in the post period.

Strategy 1: Interrupted-Time Series of cash-related incidents in Buses

The use of time series evidence has been controversial in the crime literature; especially regarding the empirical estimates of the deterrent effect of capital punishment on homicides.

\textsuperscript{17}See (Domínguez and Asahi, 2016) for an analysis of variations in crime patterns associated with each day of the week.

\textsuperscript{18}UN Office on Drugs and Crime, 2014
Chapter 2. How Potential Offenders and Victims Interact

Table 2.1: Robberies reported in Buses and Public Space-Streets for different periods.

<table>
<thead>
<tr>
<th></th>
<th>Buses</th>
<th></th>
<th>Street and Public Spaces</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NonCash Mean</td>
<td>St.Dev</td>
<td>Cash Mean</td>
<td>St.Dev</td>
</tr>
<tr>
<td>Pre</td>
<td>12.40 (0.77)</td>
<td>11.38 (0.68)</td>
<td>346.88 (7.90)</td>
<td>139.76 (3.04)</td>
</tr>
<tr>
<td>Transition</td>
<td>14.65 (0.54)</td>
<td>28.18 (1.39)</td>
<td>403.57 (7.53)</td>
<td>141.13 (1.70)</td>
</tr>
<tr>
<td>Post</td>
<td>14.04 (0.35)</td>
<td>3.76 (0.16)</td>
<td>409.19 (4.79)</td>
<td>124.89 (1.80)</td>
</tr>
</tbody>
</table>

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

Source: Own elaboration using Undersecretary of Crime Prevention, Carabineros de Chile

in the United States where the choice of time period analyzed has led scholars to different conclusions\(^{19}\). However, in this case the variation is arguably exogenous. Figure 2.3 shows the evolution of cash-related robbery incidents reported on buses. A simple look at the time series pattern suggest that the pattern of Table 2.1 is more pronounced for this subgroup of crimes. During the transition period (October, 2005 to February, 2007) cash-related incidents grew 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 then they remained stable at a very low level for the following three years.

Hence, our first approach is a pre and post comparison using a long time series of all cash-robbery crimes reported as occurring on a bus. We run the following regression:

\[
Crime_t = \alpha + \beta_1 Transition_t + \beta_2 Post_t + \beta_3 PSCrime_t + \omega_{m(t)} + \epsilon_t \tag{2.8}
\]

\(Crime_t\) represents the number of crime incidents reported in buses in week \(t\). Importantly, all crime categories used in the regression in this article 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\(^{20}\). This particular denominator will allow us to interpret regression coefficients in percentage terms.

\(^{19}\)For an overview of this topic and the main flaws of empirical estimates commonly cited in the literature, we suggest Donohue and Wolfers, 2006 and Nagin, 2013.

\(^{20}\)The exact population who was at risk on buses is very difficult to measure; it should consider not only the daily rate of passengers but also the number that were riding a bus at any moment. Unfortunately, temporally granular data on ridership is 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. A similar 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 week divided by the average weekly incidence in the jurisdiction during the sample period.
CHAPTER 2. HOW POTENTIAL OFFENDERS AND VICTIMS INTERACT

Figure 2.3: Cash-related robbery incidents reported in 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.

Transition\textsubscript{t} and Post\textsubscript{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). PScrime\textsubscript{t} is the number of incidents reported in the same category of the dependent variable (considering place of the incident and whether the good involved in the crime was cash or not) in streets and public spaces in the week t. Finally, \( \omega_{m[t]} \) is a month fixed effect.

Strategy 2: Difference in differences within Buses

A reasonable concern regarding strategy 1 is that we do not control for ridership in each period. This concern can be particularly important for the estimation of the coefficient associated with the post-reform period since it may confound the variation imposed by the endogenous changes in ridership induced by the fare integration with Metro system. We would ideally like to control for weekly ridership levels, effectively normalizing our crime measure by utilization volume. Unfortunately, ridership data is not available and thus inevitably our estimates based on pre and post comparison will be unable to separate the
effects due to changes in incentives from the effects due to changes in ridership. Including month fixed effects and crimes reported in the public space may control for some seasonal pattern but it will not fully address a possible new ridership pattern induced by the policy\textsuperscript{21}.

Instead, we implement a difference in differences (DD) approach incorporating non-cash robbery incidents in the regression. If we assume that in terms of ridership non-cash robbery incidents (for example, robbery of cellphones or other consumer electronics) follow a similar pattern than cash-robbery incidents, and that this pattern was not altered during that period for other reason than the reform to the payment system, we can identify the effect of this reform.

Figure 2.4 shows the evolution of both time series. In the pre-reform period both curves show a similar patterns. Beginning with the transition period, these series move in opposite directions. During the transition period the number of cash incidents, relative to noncash incidents increased dramatically. By contrast, during the post-reform period cash-related incidents dropped dramatically and the gap between the two curves remained remarkably stable during this entire three years period. Notably, non-cash 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, we propose the following diff-in-diff regression to estimate those coefficients:

\[
Crime_{it} = \alpha + \beta_1 Trans_t + \beta_2 Post_t + \beta_3 Cash_i + \beta_4 Cash_i \times Trans_t + \beta_5 Cash_i \times Post_t + \omega_{m(t)} + \epsilon_{it} \tag{2.9}
\]

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). This approach relies on the common trend assumption which requires that in the absence of the policy both crime totals would

\textsuperscript{21}In order to analyze the magnitude of this issue we present in the appendix section detailed information from the Santiago origin-destination survey (Encuesta Origen Destino). A simple comparison between the available years suggest at least two relevant facts. First, there is no important variation in bus ridership between 2001 and 2006. This is consistent with the fact that there were no perceived differences from the passengers’ point of view between the pre-reform and transition period other than the way drivers were compensated. However, the introduction of the new payment system and Metro integration during the post-reform period arguably modified the ridership level of both Metro and buses. Unfortunately, the best available data for that analysis is the 2012 version of the origin-destination survey. During these six-year period we observe a 20% decrease in the number of trips using some bus combination from 24% to 19% which coincides with a similar increase in Metro ridership. Importantly, this entire variation cannot be exclusively attributed to the introduction of the fare integrated system since also Metro was expanded from 66 to 100km during the same period. We can argue that the variation in the number of noncash reported incidents is closely associated with the number of people riding buses, so a difference in differences approach that exploits this variation can offer a tractable general solution to this issue. The only assumption for the validity of this approach is that noncash robbery incidents follow a similar pattern than cash-robbery incidents, and that the only reason that this pattern might have been altered was precisely a reform on the payment system that could have made cash less available. In any case, the large magnitude of the post-reform coefficient, regardless the approach chosen, cannot be captured by this kind of variation in the ridership level.
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Figure 2.4: Robbery incidents reported in buses. Cash and non-cash related incidents. 2005-2010

[Graph showing trends in robbery incidents reported in buses from 2005 to 2010, with cash and non-cash incidents distinguished by lines.]

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

follow similar trajectories. This assumption allows us to identify as the effect on crime associated with the policies adopted during the post-reform period relative to the pre-reform period. In a similar way, we can interpret as the effect on crime associated with the policy changes implemented during the transition period.

Strategy 3: Triple differences in Buses relative to Public Spaces in Santiago

As we have just discussed, valid estimates of the difference in differences coefficients require that both crime categories would evolve similarly in expectation; this means that on average the proportional split between cash and no-cash incidents reported in buses remained stable during the period of analysis. Based on the fact that we are looking to a long period of analysis, another possible concern might be the confounding presence of a more general trend affecting the proportion of incidents on each crime category compared in Figure 2.4. In
CHAPTER 2. HOW POTENTIAL OFFENDERS AND VICTIMS INTERACT

particular, if any of the periods of analysis coincides with a trend that affected the proportion of cash and non-cash related incidents in a broad sense our common trend assumption will be violated.

In order to address this issue, we implement a third strategy using triple differences. To the extent that the observed differences in the proportion of cash and non-cash related incidents affected incidents in public spaces and buses alike, we can control for those differences, and finally identify the causal parameter of the relationship. We propose a triple differences approach incorporating robbery incidents reported in the public space in Santiago. This estimation does not require that both crime categories would evolve in a similar way, but that any secular trend in the proportional split of robberies between cash and non-cash incidence be similar for robberies on buses and robberies in public spaces.

Figure 2.5 shows the evolution of robbery incidents (cash and non-cash) reported in public spaces and streets for our period of analysis. At least, two main features can be highlighted from this figure. First, as in the case of buses, it shows a seasonal pattern; the period between July and October has the highest incident level, which is consistent with the way regular activities are developed in a city like Santiago. Second, during the first three years, cash-related incidents are very stable around 150 incidents per week but it decreased to 110 incidents per week in the last year. Again, the presence of possible confounders during that same period should be addressed.

In addition, by simply comparing figures 2.4 and 2.5 we can get a sense of the frequency of incidents on buses relative to street and public spaces. During the pre-reform period, the proportion of cash-robberies incidents in buses (Figure 2.4) represents a considerable portion of the total incidents, and is equivalent to 10% of the incidents reported in street and public space in the same crime category. A similar analysis in Figure 2.5 shows a substantial lower level of non-cash-related incidents in buses relative to the public space. In that sense, among the total robberies reported in buses, cash-related incidents represent a significantly higher proportion, around 50% of the total, relative to the 25% of the same proportion when comparing to robberies reported in streets and public spaces.

I propose the following triple differences regression:

\[
Crime_{ijt} = \alpha + \ldots + \beta_{10} T_{t} \times Cash_{i} \times Bus_{j} + \beta_{11} P_{t} \times Cash_{i} \times Bus_{j} + \omega_{m(t)} + \epsilon_{ijt} \tag{2.10}
\]

I wrote a simplified version of the model which actually includes several interacted terms for both period of analysis as in the previous specification models. In this case i represents the type of crime (cash or noncash), j represents the place (bus or public spaces), and t the period associated with each observation. From this estimation, we can recover which represents the effect of removing the cash-payment system from buses. In a similar way, we can estimate a triple difference coefficient associated with the transition period. Importantly, I normalized all crime categories relative to the pre-period level.

\footnote{During summer season (especially between December and February) schools and colleges are closed, and is the time of the year where most of the people spend their vacations.}
Figure 2.5: Robbery incidents reported in streets and public spaces. Cash and non-cash related incidents. 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.

2.6 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 the appendix section.

Interrupted Time-Series estimates

Table 2 shows the basic coefficients using time-series regressions. The dependent variable is defined as the weekly number of reported incidents divided by average weekly incidents.
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...during the pre-reform period\(^{23}\). Thus, each coefficient can be read as the percentage change in crime for each period relative to the level during the pre-period in the same crime category. In the first two columns for the non-cash robbery regressions, coefficients are around 10\% and 5\% higher relative to the pre-reform period, but none of those differences are significant. For cash robberies, however, there are large and important changes relative to the pre-period. Relative to the pre-period, the transition period had 150\% more incidents reported on buses, and this coefficient remains robust to the inclusion of incidents reported in the public space as control. On the other hand, the post period coefficient is -0.6 which means that incidents in that crime category where 60\% lower to the pre-reform period. This coefficient is robust to the inclusion of crime in the public space as control. In addition to reporting robust standard errors, we include in the appendix Newey-West estimates using different number of lags. Moreover, we perform permutation exercises to empirically test how likely is to find those estimates by chance. Figures 2.8-2.11 in the appendix describe those estimates.

Table 2.2: Interrupted time series estimates. Robbery in Buses

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-Cash</td>
<td>Non-Cash</td>
<td>Cash</td>
<td>Cash</td>
</tr>
<tr>
<td>Transition</td>
<td>0.155*</td>
<td>0.108</td>
<td>1.521***</td>
<td>1.522***</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.070)</td>
<td>(0.120)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>Post</td>
<td>0.0923</td>
<td>0.0459</td>
<td>-0.673***</td>
<td>-0.616***</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.060)</td>
<td>(0.060)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Robb_PS</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Pre-reform Level of DV</td>
<td>12.40</td>
<td>12.40</td>
<td>11.38</td>
<td>11.38</td>
</tr>
<tr>
<td>N</td>
<td>314</td>
<td>314</td>
<td>314</td>
<td>314</td>
</tr>
<tr>
<td>R-sq</td>
<td>0.297</td>
<td>0.307</td>
<td>0.786</td>
<td>0.792</td>
</tr>
</tbody>
</table>

Notes: Coefficients are calculated using interrupted time-series on each crime category. Robb\(_{PS}\) represents robberies in the same crime category (cash or non-cash 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. Newey-West estimates using different number of lags are in the Appendix. * \(p<0.05\), ** \(p<0.01\), *** \(p<0.001\)

\(^{23}\)Many results are replicated under different model specifications including the way the dependent variable is coded, including count models (Poisson), and OLS-regression using log-crime as the dependent variable. For details, see Appendix Tables 2.7-2.11
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Difference in differences and Triple Differences estimates

As we discussed earlier, our estimates of the effects of the various stages of implementation of Transantiago may be confounded by changes in ridership. Our strategy is to test for a differential change in crimes involving cash from other crime occurring on buses. As other crime will also be affected by changes in ridership, looking for a departure between two bus-related crime series indirectly adjust for potential changes in ridership.

Table 2.3 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% on reported incidents relative to the pre-reform levels. Similarly, coefficients for the post-reform period are significant but the different specifications show some important differences. Results in columns 1 and 2 suggest that coefficient for post-reform period is sensitive to the length of the period considered. In order to control for some secular trend that might be affecting the proportion of cash-robbery relative to noncash robbery incidents I include estimates in columns 3 and 4 from triple differences regressions. They suggest that part of the large coefficient in column 1 is capturing a broader reduction in the proportion of cash-related incidents. In any case, in all specifications the large and substantial reduction on cash-related robberies persists. We also perform permutation test for these set of results. Figures 2.8-2.11 in the appendix present those results.

Table 2.3: Double and Triple Differences estimates. Robbery

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

Notes: Coefficients are obtained from double-diff and triple-diff regressions including monthly fixed effects. All weeks are included in the first and third columns, and a restricted sample was used in the second and fourth columns excluding observations of years 2009 and 2010 (n2=52x2x4; n4=52x2x4x2). 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

Finally, in order to assess the validity of the research design I run an event-study model which provide a more transparent description of the estimates reported in Table 2.3. In
essence, I modify equation (3.5) by interacting the cash-category indicator with month specific indicators instead of a single indicator for the transition and post-reform period.

\[
Crime_{it} = \alpha + \beta Cash_i + \sum_{i}^{T} \gamma_i I[i = t] + \sum_{i}^{T} \delta_i I[i = t] \times Cash_i + \omega_{m(t)} + \epsilon_{it} \tag{2.11}
\]

The coefficient of interest from equation (2.11) are the value of \(\delta\) estimates which are displayed in Figure 2.6. As it is usual in event studies I normalize to drop the coefficient for the year prior to the first policy change (transition period).

Figure 2.6: Event-study: Cash-category interacted with Month specific indicators: 2005-2010

Notes: Lines represent the evolution of the interacted coefficients \(\delta\) of equation (2.11) which represent the monthly effect on cash-related robberies reported at buses in Santiago. Vertical dashed lines show the beginning of the transition (October, 2005) and the post-reform (February, 2007) periods.

The results displayed in Figure 2.6 confirms the results of Table 2.3 that the transition period lead to a large increase in cash-related incidents that almost disappeared during the post-reform period. In the Appendix section, I plotted histograms 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.
2.7 Victim’s resistance and the Threat of Lethal Force

In addition to the effect on overall criminal activity, I analyze the extent to which the offenders-victim’s 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 the nature rather than the level of crime. This is an important dimension in criminal analysis where the empirical evidence is still scarce. Recent developments in the cost of crime literature emphasize that benefit-cost calculations are very sensitive to the impacts of policy on violent crime, especially crimes resulting in fatalities (Chalfin and McCrary, 2013; Domínguez 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’s 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 empirically testing the model prediction for the transition period where more but less violent crime happened.

Main prediction: Fixed salary policy lead 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 on the incidents reported to the police. In particular, 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 a 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 appendix section 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 is used in the robbery. By assuming a certain distribution of $m_i$, we can easily compare $P_F$ for each period.

$$P_F = \Pr[U_F > U_K] = \Pr[m_i < G \times (P_{SF}(G_d) - P_{SK}(G_d)) - S_F + S_K] \quad (2.12)$$
During the transition period, we know that $G_D$ (driver’s loses) was decoupled from $G$ (offender’s expected gains). Basically, the model predicts very plausible condition under which the transition period lead 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:

$$P_{SK}(G_d) - P_{SK}(G) > P_{SF}(G_d) - P_{SF}(G)$$  \hspace{1cm} (2.13)

(2.13) depends on how chances of being successful vary between the pre-period and the transition period. In the appendix section, I discuss the specific conditions required this prediction of the model. 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 to drivers to resist (their pay no longer depends on the outcome of the robbery) offenders substitute towards less lethal threats (e.g. knives).

**Gun Robberies vs. the Use of Less Lethal Weapons**

Figure 2.7 shows the evolution of cash-related robberies in 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 empirically test a significant variation in the proportion of gun-related incidents I run the following regression:

$$Prop.Firearm_t = \alpha + \beta_1 Transition_t + \beta_2 Post_t + \omega_m(t) + \epsilon_t$$ \hspace{1cm} (2.14)

Table 2.4 shows the results for regression (2.14). Transition period is associated with a significant 8% decline in the proportion of firearm-incidents. This finding is consistent to other specifications \(^\text{24}\). Although this period experienced a large increase in criminal activity, most of the increase is 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 I am less confident about this variation since it 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 2.4 confirms the model prediction that the increase in criminal activity associated with the change on driver’s incentives to resist also modified the level of violence drivers were exposed to during the transition period. As a robustness check, in the appendix Table 2.16 I present results from similar regressions using non-cash related incidents reported in buses for the same period, and I find no significant results in terms of the weapon used in the incident.

\(^{24}\)See Tables 2.14 and 2.15 in the Appendix section
Figure 2.7: Monthly evolution robbery cash-related incidents in Buses by Weapon used 2005-2010

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

Finally, Table 2.5 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 victim 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 transition period, we may expect that the proportion of them that were injured when robbed declined.
Table 2.4: Time-series estimates: Proportion of Firearm incidents. Cash robbery in buses

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

Notes: Coefficients are calculated 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 in buses. Robust standard errors are reported parentheses. Newey-West estimates using different number of lags are in the Appendix. * p<0.05, ** p<0.01, *** p<0.001
Table 2.5: Proportion of Victims that report some injury by each crime-weapon category. Cash-related incidents

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No Weapon</td>
<td>0.333</td>
<td>0.3</td>
<td>0.150</td>
<td>1.3</td>
<td>0.286</td>
<td>0.1</td>
</tr>
<tr>
<td>Firearm</td>
<td>0.083</td>
<td>23.0</td>
<td>0.073</td>
<td>44.9</td>
<td>0.108</td>
<td>6.9</td>
</tr>
<tr>
<td>Knife</td>
<td>0.114</td>
<td>25.4</td>
<td>0.071</td>
<td>69.3</td>
<td>0.154</td>
<td>8.4</td>
</tr>
<tr>
<td>Stick</td>
<td>0.300</td>
<td>1.3</td>
<td>0.235</td>
<td>3.4</td>
<td>0.321</td>
<td>0.6</td>
</tr>
<tr>
<td>Threat</td>
<td>0.333</td>
<td>2.5</td>
<td>0.290</td>
<td>4.6</td>
<td>0.398</td>
<td>2.4</td>
</tr>
<tr>
<td>Other</td>
<td>0.333</td>
<td>1.2</td>
<td>0.074</td>
<td>3.6</td>
<td>0.207</td>
<td>0.6</td>
</tr>
<tr>
<td>Total [Inc/Month]</td>
<td>53</td>
<td>127</td>
<td>19</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

Table 2.5 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 the almost no variation in firearm-crime category reinforces the model prediction of heterogeneous weapon return variation imposed by the new policy regime. A similar comparison displaying results for noncash crime category is in the Appendix Table 2.17 where no similar pattern is found.
2.8 Conclusion

This paper presents a formal model where the observed crime rate is determined by the interaction between potential offenders and victims. The role of the former has been studied extensively in many empirical applications while the behavior of victims has received considerably less attention. Although assuming no substantial variation or behavioral response from the victim’s side might be reasonable in certain circumstances, it is unlikely to be plausible in many situations and may obscure important behavioral responses that generate unintended consequences of policy reforms. The model that I present in this paper can be informative to understand both the level and nature of crime.

I empirically test the model predictions exploiting the specific features of a sequential set of reforms implemented in the public transport sector in Santiago, Chile. Transantiago was a very ambitious plan that modified the bus system in a radical way. This article does not represent an exhaustive evaluation of the program but rather takes advantages of its main features to learn about criminal activity. Given the scope of the reform, I focus the analysis on the factors that most likely affect crime. For example, I argue that the total variation in criminal activity reported in buses was not severely affected by other elements also incorporated with Transantiago such as the gradual introduction of new buses (after October, 2005) or new bus routes (after February, 2007). If those factors affected the likelihood or incidence of a highly violent crime as robbery, our estimates should be better interpreted as the overall effect of the reform implementation on crime. However, we can be confident about the direction and interpretation of the results for several reasons. First, all estimates rely on data collected by an independent agency as the Chilean police, and I restrict the analysis to a violent crime (robbery) where around 70% to 90% of the cases involves a lethal weapon. In addition, the bus system represents a crucial transportation mode for a major portion of the population (about 25% of total trips) that could not have changed substantially their travel patterns substantially (other than incorporating some Metro combination in a portion of the trip only during the post-reform period). In any case, the difference-in-difference research design accounts for most of these concerns by assuming that any variation affected similarly cash and noncash-related robberies. Finally, the large magnitude of the results, and the consistency under different identification strategies (interrupted time series, difference in differences, and triple differences) can be considered as evidence of robustness of the empirical approach.

There are two main empirical findings. First, I find that the crime rate is quite sensitive to victim incentives and behavior. I argue that driver’s incentives affect the level of effort they devote to protect a very attractive target for criminal purposes such as the amount of money in fare collection boxes inside buses. During the period where drivers’ salaries were strictly attached to the money collected we observe a relatively small rate of cash-related robberies in buses. By contrast, I find a large increase in robberies for the period when drivers started to be paid fixed salaries. Relative to available estimates in the economics of crime literature this finding suggests that private behavior is an important omitted variable in understanding victimization. To put the magnitude in perspective, consider the following
thought experiment. What size increase in police presence on buses would be needed to offset the impact associated with drivers exhibiting less resistance? Assuming a crime-police elasticity estimate of -0.3 (Di Tella and Schargrodsky, 2004), the overall crime reduction associated with a high-protection strategy adopted by drivers in the pre-reform period would be compensated by a 200% increase in police presence.

Alternatively, we can use this estimate along with some insights provided by the potential offender-victim model to see how much victims contribute to deter criminals from offending. If we make some basic assumptions to make the reaction functions tractable, we can see that the overall response in terms of crime increase during the transition period suggests that a high-resistance strategy of a driver may reduce offender’s probability of success from 1 (under the low-resistance strategy) to 0.4 (under the high-resistance strategy).

Although this result suggests that victims can do a lot to prevent criminals from offending, this could of course come at a very high personal cost. During the pre-reform period of a relatively low crime rate, we also notice that drivers were exposed to a higher level of violence conditioning on being robbed. This is an additional prediction of the model when incorporating offender’s weapon choice in the attack. I show that an exogenous variation in victim’s likelihood to resist may induce differential responses in terms of the level of violence adopted by the offender. Specifically, I find a higher proportion of attacks using a less lethal weapon at the same time when drivers drastically reduced their level of resistance. Further, this finding is reinforced by the fact that conditioning on being attacked with a particular weapon, drivers were less likely to report some injuries during the transition period, and that variation was larger for less lethal weapons.

An additional important result is that the eradication of cash-transactions caused a dramatic decline in crime. Although the results are associated with a specific setting such as cash-related incidents in buses, I believe it has some important implications for other crime settings. In fact, a decline in the use of cash in everyday life transactions has been suggested as an alternative explanation for the great American crime decline. However, the empirical literature is far from having collected a sufficient amount of credible evidence as a proof of the case. This study offers specific evidence on this regard, although the effect is local. A reasonable caveat is that we cannot rule out all possible ways of displacement towards other crime activities (e.g. noncash robberies or other crimes such as burglary), or places that this reform might have induced. However, given the consistency and large magnitude of the coefficient it seems unlikely that all the observed reduction was reallocated to other criminal

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25 This might be a conservative estimate since in the case of Di Tella and Schargrodsky (2004) represents the effect on vehicle theft. Chalfin and McCrary (2013) suggest a -0.56 estimate for robbery.

26 See Appendix 2.9 for details

27 This limitation is particularly important for generalizing this effect to other settings. Interestingly, Clarke refers to this case to argue that any claim for crime reduction in the long-run should be taken cautiously since the same cause that is reducing crime in the short-run may also offer other unexpected opportunities in the future: “the movement to a “cashless” society in which financial transactions are largely computerized would greatly reduce the scope of petty pilfering but could create opportunities for crime of a very different order large scale computer fraud” (R. V. Clarke, 1983, p.247)
In order to get a sense of the magnitude of the effect of eliminating cash transactions we can use again the Di Tella and Schargrodsky (2004) crime-police elasticity estimate, and considering that 30% of street robberies are cash-related incidents, our estimate would be equivalent to a 70% increase in police presence in streets and public spaces. Although the magnitude of this estimate is lower than the “moral hazard” effect associated with victim’s behavior, it offers a plausible policy intervention that can significantly reduce the availability of a salient criminal opportunity which may ultimately deter potential criminals from offending at the level of a large public investment.

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 U.S. 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 effective crime prevention tool, open fare collection boxes are still present in the public transport sectors of a large number of 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 transport system, 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 the open fare collection boxes in place, even at the expense of a higher risk of violence and victimization. From the bus owner’s perspective, this kind of system may encourage drivers to directly control fare evasion which is a common problem in the public transport sector. At the same time, from the drivers’ point of view, open fare collection boxes may allow them to increase their salaries by charging a lower fare to those passengers willing to ride without a ticket. A light regulation in the public transport sector can do little to incentivize the implementation of simple crime-prevention measures. In this case, the final product is the persistent presence of a highly attractive target for criminal purposes. This specific case has allowed us to discuss how such incentives may affect both the level and nature of crime. In a similar way, we believe that a deeper understanding about agent’s incentives in other settings would help us to analyze the specific characteristics of the criminal activity and how to reduce it at the optimum level.
2.9 Appendix

Table 2.6: Transport mode evolution in Santiago, Chile

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

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

Table 2.7: Newey-West regression estimates. Robbery in Buses: Non-Cash Incidents

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

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 no-cash 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 parentheses. * p<0.05, ** p<0.01, *** p<0.001
Table 2.8: Newey-West regression estimates. Robbery in Buses: Cash Incidents

<table>
<thead>
<tr>
<th></th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition</td>
<td>1.521***</td>
<td>1.521***</td>
<td>1.521***</td>
<td>1.521***</td>
<td>1.521***</td>
</tr>
<tr>
<td></td>
<td>(0.148)</td>
<td>(0.200)</td>
<td>(0.277)</td>
<td>(0.319)</td>
<td>(0.285)</td>
</tr>
<tr>
<td>Post</td>
<td>-0.673***</td>
<td>-0.673***</td>
<td>-0.673***</td>
<td>-0.673***</td>
<td>-0.673***</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.063)</td>
<td>(0.068)</td>
<td>(0.064)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Robb_PS</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td># Lags</td>
<td>1</td>
<td>4</td>
<td>12</td>
<td>26</td>
<td>52</td>
</tr>
<tr>
<td>N</td>
<td>314</td>
<td>314</td>
<td>314</td>
<td>314</td>
<td>314</td>
</tr>
</tbody>
</table>

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 no-cash 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 parentheses. * p<0.05, ** p<0.01, *** p<0.001
Table 2.9: Newey-West regression estimates. Robbery in Buses: Cash Incidents

<table>
<thead>
<tr>
<th></th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition</td>
<td>1.522*** (0.146)</td>
<td>1.522*** (0.196)</td>
<td>1.522*** (0.272)</td>
<td>1.522*** (0.313)</td>
<td>1.522*** (0.280)</td>
</tr>
<tr>
<td>Post</td>
<td>-0.616*** (0.065)</td>
<td>-0.616*** (0.066)</td>
<td>-0.616*** (0.074)</td>
<td>-0.616*** (0.066)</td>
<td>-0.616*** (0.045)</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Robb_PS</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># Lags</td>
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<td>4</td>
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<td>314</td>
<td>314</td>
<td>314</td>
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</tbody>
</table>

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 no-cash 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 parentheses. * p<0.05, ** p<0.01, *** p<0.001
Figure 2.8: Permutation Tests: Pre vs. Transition period. Time Series approach

Notes: Figure represents a histogram of the distribution of 184,756 permutations of the treatment status among pre-period and transition period months. For the permutation sample, we include a similar group of months for each period. In particular, we include the ten months that were available for the pre-period, and consistently include ten months of the transition period using the same months of the year. Blue line represents the average of the difference between the two comparison groups using the actual treatment status. Coef = 1.67422; P-value = 2.706272e-05
Figure 2.9: Permutation Tests: Pre vs. Post period. Time Series approach

Notes: Figure represents a histogram of the distribution of 48,620 permutations of the treatment status among pre-period and transition period months. For the permutation sample, we include a similar group of months for each period. In particular, we include the ten months that were available for the pre-period, and consistently include ten months of the transition period using the same months of the year. Blue line represents the average of the difference between the two comparison groups using the actual treatment status. Coef = -0.5494756; P-value = 0.000431921
Figure 2.10: Permutation Tests: Pre vs. Transition period. DD approach

Notes: Figure represents a histogram of the distribution of 184,756 permutations of the treatment status among pre-period and transition period months. For the permutation sample, we include a similar group of months for each period. In particular, we include the ten months that were available for the pre-period, and consistently include ten months of the transition period using the same months of the year. Blue line represents the average of the difference between the two comparison groups using the actual treatment status. Coef = 1.503243; P-value = 1.623763e-05
Figure 2.11: Permutation Tests: Pre vs. Post period. DD approach

Notes: Figure represents a histogram of the distribution of 48,620 permutations of the treatment status among pre-period and transition period months. For the permutation sample, we include a similar group of months for each period. In particular, we include the ten months that were available for the pre-period, and consistently include ten months of the transition period using the same months of the year. Blue line represents the average of the difference between the two comparison groups using the actual treatment status. Coef = -0.500228; P-value = 0.00211847
CHAPTER 2. HOW POTENTIAL OFFENDERS AND VICTIMS INTERACT

Model 1. Potential offender and victim’s interaction

Fixed salary policy lead to an increase in crime

Proof of declining in the offenders probability of success:

\[ P_S \equiv P_S(t = pre) < P_S(t = tra) \equiv P'_S \]

\[ H(G)P_H + (1 - H(G))P_L < H(G_d)P_H + (1 - H(G_d))P_L \]

\[ H(G_d)(P_L - P_H) < H(G)(P_L - P_H) \]

\[ H(G \times d) < H(G) \]

Which comes from the fact that drivers are less likely to resist in the transition period: \( H(tra) < H(pre) \) which is true for any \( d < 1 \).

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.

\[ Pa(t = pre) \equiv P(b_i < P_S G - S) > P(b_i < P''_S G_o - S) \equiv Pa(t = post) \]

\[ P_S G - S > P''_S G_o - S \]

\[ P_S G > P''_S G_o \]

\[ G(P_L - H(P_L - P_H)) > G_o(P_L - H''(P_L - P_H)) \]

\[ G(P_L - \Omega[G(P_L - P_H)\{P_L - P_H\}] > G_o(P_L - \Omega[G_o(P_L - P_H)](P_L - P_H)) \]

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

Alternatively, we can think that the introduction of fixed salaries along with the elimination of cash as a payment mechanism modified the choice problem for the drivers. During this period, they can directly affect the probability of attack \( P_A \) by setting offender’s expected reward \( G = G_o \). We assume that drivers know offender’s 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 \( \Psi \) is an increasing function, an equivalent problem for driver’s choice during the post-reform period is:
minimize \quad f(G_o) = G_o \times P_S(G_o)

subject to \quad G_o \geq 0

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:

\[
G^*_o = \begin{cases} 
0, \\
\frac{P_S(G)}{P_S'(G)} = \frac{p_l - (p_l - p_h)\Omega((p_l - p_h)G_o)}{(p_l - p_h)^2\Omega'((p_l - p_h)G_o)},
\end{cases}
\]

(2.15)

\( G^*_o = 0 \) 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 \( \Omega(\cdot) \). We can see that when \( G^*_o = \frac{P_S(G)}{P_S'(G)} \), the value of the objective function is \( f(G^*_o) = G^*_oP_S(G^*_o) > 0; \forall G^*_o > 0 \). A more detailed expression is given by (2.16):

\[
 f(G^*_o) = G^*_o \times P_S(G^*_o) = \left[\frac{p_l - (p_l - p_h)\Omega((p_l - p_h)G_o)}{(p_l - p_h)^2\Omega'((p_l - p_h)G_o)}\right]^2 > 0
\]

(2.16)

**Model 2. Endogenous determination of the probability of attacking**

Here I describe the theoretical responses 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:

\[
H \equiv \Pr[U_H > U_L] = \Pr[c_1 < P_A(P_L - P_H)G_d] = \Omega[P_A(P_L - P_H)G_d]
\]

(2.17)

Offenders 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 \( P_A \):

\[
P_A = \Psi[P_S G - S] \\
= \Psi[(P_H H + P_L(1 - H)) \times G - S] \\
= \Psi[(P_H H(P_A, G) + P_L(1 - H)(P_A, G))) \times G - S] \\
= \Psi[(P_H \Omega[P_A(P_L - P_H)G_d] + P_L(1 - \Omega[P_A(P_L - P_H)G_d])) \times G - S] \\
= \Psi[(P_L - (P_L - P_H) \times \Omega[P_A(P_L - P_H)G_d] \times G - S]
\]
In order to see how this function reacts to changes in the expected reward and losses experienced during the transportation reform, I simulate how driver’s probability of resist, and offender’s probability of attacking vary for different values of $G$. Figure 2.12 summarizes those responses considering five different scenarios (different discounts associated to the loses) for the transition period:

**Figure 2.12: 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.
CHAPTER 2. HOW POTENTIAL OFFENDERS AND VICTIMS INTERACT

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:

$$P_A = \Psi[(P_L - (P_L - P_H))\Omega[P_A(P_L - P_H)G] \times G - S] \tag{2.18}$$

Transition-period:

$$P'_A = \Psi[(P_L - (P_L - P_H))\Omega[P_A(P_L - P_H)G] \times G - S] \tag{2.19}$$

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 $P_A < P'_A$. We 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 $GP_A < GdP'_A$ which means that $P_A \frac{G}{G_d} < P'_A$, but since $\frac{G}{G_d} > 1$ we can re-write 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 $GP_A = GdP'_A$ 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 how large can be the variation in the probability of attacking. $P_A < P'_A \iff GP_A > GdP'_A$ 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 bus drivers although have reduced their protection level they still care about the level of risk they are being exposed to.

Alternatively, we can analyze figure 2.12. 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.

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:

$$P_A = \Psi[(P_L - (P_L - P_H))\Omega[P_A(P_L - P_H)G] \times G - S] \tag{2.20}$$

Post-period:

$$P'_A = \Psi[(P_L - (P_L - P_H))\Omega[P_A(P_L - P_H)G] \times G - S] \tag{2.21}$$
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:

$$(G - G_o)P_L > (P_L - P_H)(\Omega[(P_L - P_H)P_AG] - \Omega[(P_L - P_H)P''_A G_o])$$

for low values of $G_o \approx 0$ condition (2.22) 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.

**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, we 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 $w = \{k, f\}$:

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

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

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:

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

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

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.
$w) = P_{SW}G - S_W$. We can further incorporate a term $m_i$ which measures offender’s moral aversion of 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 is based on the following condition:

\[
\Pr[w = Firearm] = \Pr[U_F > U_K] = \Pr[m_i < G(P_{SF}(G_{BD})) - P_{SK}(G_{BD}) - S_F + S_K] \tag{2.27}
\]

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

Pre-Reform period:

\[
\Pr[U_F > U_K|t = pre] = \Theta[G(P_{SF}(G) - P_{SK}(G)) - S_F + S_K] \tag{2.28}
\]

Transition-period:

\[
\Pr[U_F > U_K|t = tra] = \Theta[G(P_{SF}(G_d) - P_{SK}(G_d)) - S_F + S_K] \tag{2.29}
\]

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

\[
P_{SF}(G_d) - P_{SK}(G_d) < P_{SF}(G) - P_{SK}(G) \tag{2.30}
\]

We can re-write that condition as:

\[
P_{SF}(G_d) - P_{SF}(G) < P_{SK}(G_d) - P_{SK}(G) \tag{2.31}
\]

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

\[
P_{SW}(G_d) > P_{SW}(G) \tag{2.32}
\]

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

Thus, condition (2.32) holds if chances for being successful when attacking with a knife vary more overt time relative to attacking with a firearm. In a sense that expression holds if the return of using a particular weapon are 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:

\[
P_{SF}(G_d) - P_{SF}(G)) < P_{SK}(G_d) - P_{SK}(G) \]

\[
H_F(G)\Delta_F - H_F(G_d)\Delta_F + P_L - P_L < H_K(G)\Delta_K - H_K(G_d)\Delta_K + P_L - P_L \]

\[
\Delta_F[H_F(G) - H_F(G_d)] < \Delta_K[H_K(G) - H_K(G_d)]
\]
Moreover, we know by assumption that \((P_{LF} - P_{HF}) < (P_{LK} - P_{HK})\), which simplify 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.

Although whether (2.32) 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 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 (2.32) 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.

\footnote{If we imposed some specific restrictions in the density function, we can analyze under which weapon the response in terms of drivers 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 2.13: Probability to resist by expected reward. Weapon = Firearm or Knife

Notes: Each line connects results from solutions implicit equations in drivers 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 2.14: Differential Probability to Resist and Attacking by Expected Reward

Notes: Each line connects results from solutions implicit equations in offenders 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 responsible for protecting during the transition period. I assume that $C$ distributes log-normal ($\text{meanlog}=3, \text{sdlog}=1$) and $B$ distributes log-normal ($\text{meanlog}=B, \text{sdlog}=1$). For the pre-reform period, I assume that disc=1 which means that expected reward equals expected loses.
Drivers resistance level implicit in our findings

In this section I plan to find the magnitude of driver’s resistance effort during the pre-reform period. Obviously, a fully description of offenders and victims require a large characterization of both agents that would require a complex calibration of several parameters. However, we can develop a simpler approximation taking advantages of our empirical findings in combination with reasonable assumptions in the structural model. The idea is to get a sense on the level of resistance opposed by the drivers that could be implicit in our results.

As we have seen in the previous sections, we have the following equations that describe our model of potential offenders and victims interaction:

\[ P_A = \Phi(P_S G_O) - S \]
\[ P_S = -H(p_L - p_H) + p_L = -H \Delta_p + p_L \]
\[ H = \Psi(\Delta_p G_D) \]

Based on our empirical findings, we have that \( P_A(t = tra) = 2.5 \times P_A(t = pre) \). If we consider that offenders heterogeneity in terms of sanction costs is captured by their opportunity costs, we can disregard \( S \) from equations 2.9. Further, if we assume that \( b_i \sim U(0, 1) \), we can rewrite \( P_A \) for the pre-reform and transition period as:

\[ P_A(t = pre) = P_A = P_S G_O \]
\[ P_A(t = tra) = P'_A = P'_S G_O \]

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 oppose any resistance \( p_L = 1 \), and that given the change of incentives for the drivers the probability of adopting a high resistance strategy for each period can be approximate 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 2.10: Interrupted Time series estimates. Robbery in Buses

<table>
<thead>
<tr>
<th>LogOLS</th>
<th>1</th>
<th>Non-Cash</th>
<th>2</th>
<th>Non-Cash</th>
<th>3</th>
<th>Cash</th>
<th>4</th>
<th>Cash</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition</td>
<td>0.183**</td>
<td>0.0699</td>
<td>0.913***</td>
<td>0.915***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.070)</td>
<td>(0.090)</td>
<td>(0.090)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td>0.0935</td>
<td>-0.0106</td>
<td>-1.108***</td>
<td>-1.021***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.060)</td>
<td>(0.080)</td>
<td>(0.090)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Robb_PS</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>314</td>
<td>314</td>
<td>301</td>
<td>301</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-sq</td>
<td>0.275</td>
<td>0.365</td>
<td>0.759</td>
<td>0.773</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Coefficients are calculated using interrupted time-series on each crime category. Robb_PS represents robberies in the same crime category (cash or no-cash related incidents). Robust standard errors are reported parentheses.* p<0.05, ** p<0.01, *** p<0.001.
Table 2.11: Interrupted Time series estimates. Robbery in Buses

<table>
<thead>
<tr>
<th>Poisson</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-Cash</td>
<td>Non-Cash</td>
<td>Cash</td>
<td>Cash</td>
</tr>
<tr>
<td>Transition</td>
<td>0.144* (0.060)</td>
<td>0.102 (0.060)</td>
<td>0.956*** (0.060)</td>
<td>0.947*** (0.060)</td>
</tr>
<tr>
<td>Post</td>
<td>0.0888 (0.050)</td>
<td>0.0483 (0.060)</td>
<td>-1.101*** (0.070)</td>
<td>-1.030*** (0.070)</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Robb_PS</td>
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<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>314</td>
<td>314</td>
<td>314</td>
<td>314</td>
</tr>
<tr>
<td>Pseudo R-sq</td>
<td>0.083</td>
<td>0.086</td>
<td>0.623</td>
<td>0.628</td>
</tr>
</tbody>
</table>

Notes: Coefficients are calculated using interrupted time-series on each crime category. Robb_PS represents robberies in the same crime category (cash or no-cash related incidents). Robust standard errors are reported parentheses.* p<0.05, ** p<0.01, *** p<0.001.
Table 2.12: Diff-in-diff and Triple diff estimates. Robbery, Santiago.

<table>
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<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-OLS Trans x Cash</td>
<td>0.730***</td>
<td>0.730***</td>
<td>0.866***</td>
<td>0.866***</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.100)</td>
<td>(0.110)</td>
<td>(0.110)</td>
</tr>
<tr>
<td>Post x Cash</td>
<td>-1.206***</td>
<td>-1.016***</td>
<td>-0.921***</td>
<td>-0.788***</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.100)</td>
<td>(0.110)</td>
<td>(0.110)</td>
</tr>
<tr>
<td>N</td>
<td>615</td>
<td>413</td>
<td>1243</td>
<td>829</td>
</tr>
<tr>
<td>R-sq</td>
<td>0.738</td>
<td>0.745</td>
<td>0.963</td>
<td>0.971</td>
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</table>

Notes: Coefficients are calculated using interrupted time-series on each crime category. Columns two and four consider a restricted sample (Year < 2009). Robust standard errors are reported parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Table 2.13: Diff-in-diff and Triple diff estimates. Robbery, Santiago.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poisson Trans x Cash</td>
<td>0.740***</td>
<td>0.740***</td>
<td>0.882***</td>
<td>0.882***</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.080)</td>
<td>(0.100)</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Post x Cash</td>
<td>-1.232***</td>
<td>-1.020***</td>
<td>-0.954***</td>
<td>-0.795***</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.090)</td>
<td>(0.100)</td>
<td>(0.100)</td>
</tr>
<tr>
<td>N</td>
<td>628</td>
<td>416</td>
<td>1256</td>
<td>832</td>
</tr>
<tr>
<td>Pseudo R-sq</td>
<td>0.175</td>
<td>0.164</td>
<td>0.949</td>
<td>0.954</td>
</tr>
</tbody>
</table>

Notes: Coefficients are calculated using interrupted time-series on each crime category. Columns two and four consider a restricted sample (Year < 2009). Robust standard errors are reported parentheses. * p<0.05, ** p<0.01, *** p<0.001.
Figure 2.15: Histogram: Density of the event-study coefficients: 2005-2010

Notes: Figures represent the density function of the interacted coefficients $\delta$ of equation (2.11) 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 shows the value of the coefficient from regression 3.5.
Figure 2.16: Histogram: Density of the event-study coefficients: 2005-2010

Notes: Figures represent the density function of the interacted coefficients $\delta$ of equation (2.11) 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 shows the value of the coefficient from regression 3.5.
Table 2.14: Newey-West estimates. Proportion of Firearm-robberies in Buses: Cash

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition</td>
<td>-0.0877**</td>
<td>-0.0877***</td>
<td>-0.0877***</td>
<td>-0.0903**</td>
<td>-0.0903***</td>
<td>-0.0903***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.018)</td>
<td>(0.013)</td>
<td>(0.028)</td>
<td>(0.017)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Post-Reform</td>
<td>-0.0903**</td>
<td>-0.0903**</td>
<td>-0.0903**</td>
<td>-0.0980**</td>
<td>-0.0980**</td>
<td>-0.0980**</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.028)</td>
<td>(0.027)</td>
<td>(0.031)</td>
<td>(0.034)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Month FE</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>YEAR&lt;=2008</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
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<tr>
<td># Lags</td>
<td>1</td>
<td>12</td>
<td>24</td>
<td>1</td>
<td>12</td>
<td>24</td>
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<tr>
<td>N</td>
<td>72</td>
<td>72</td>
<td>72</td>
<td>72</td>
<td>72</td>
<td>72</td>
</tr>
</tbody>
</table>

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

Table 2.15: Newey-West estimates. Proportion of Firearm-robberies in Buses: Cash

<table>
<thead>
<tr>
<th></th>
<th>7</th>
<th>8</th>
<th>9</th>
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<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition</td>
<td>-0.0877**</td>
<td>-0.0877***</td>
<td>-0.0877***</td>
<td>-0.0781*</td>
<td>-0.0781**</td>
<td>-0.0781***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.019)</td>
<td>(0.013)</td>
<td>(0.031)</td>
<td>(0.026)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Post-Reform</td>
<td>-0.0332</td>
<td>-0.0332</td>
<td>-0.0332*</td>
<td>-0.0318</td>
<td>-0.0318</td>
<td>-0.0318*</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.019)</td>
<td>(0.013)</td>
<td>(0.031)</td>
<td>(0.026)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Month FE</td>
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<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>YEAR&lt;=2008</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td># Lags</td>
<td>1</td>
<td>12</td>
<td>24</td>
<td>1</td>
<td>12</td>
<td>24</td>
</tr>
<tr>
<td>N</td>
<td>48</td>
<td>48</td>
<td>48</td>
<td>48</td>
<td>48</td>
<td>48</td>
</tr>
</tbody>
</table>

Notes: Newey-West coefficients are calculated using interrupted time-series on each crime category. Robust standard errors are reported parentheses. * p<0.05, ** p<0.01, *** p<0.001.
Table 2.16: Interrupted Time-series estimates: Proportion of Firearm incidents in buses. Non-cash robbery

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Transition</td>
<td>-0.0428</td>
<td>-0.0471*</td>
<td>-0.0428</td>
<td>-0.0434</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.023)</td>
<td>(0.023)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Post-Reform</td>
<td>0.0342</td>
<td>0.0319</td>
<td>0.0438</td>
<td>0.0422</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.021)</td>
<td>(0.025)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Month FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>YEAR&lt;2008</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td>72</td>
<td>72</td>
<td>48</td>
<td>48</td>
</tr>
<tr>
<td>Pseudo R-sq</td>
<td>0.201</td>
<td>0.345</td>
<td>0.266</td>
<td>0.385</td>
</tr>
</tbody>
</table>

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

Table 2.17: Proportion of Victims that report some injury by each crime-weapon category. NonCash-related incidents

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No Weapon</td>
<td>0.077</td>
<td>1.3</td>
<td>0.120</td>
<td>1.7</td>
<td>0.306</td>
<td>1.3</td>
</tr>
<tr>
<td>Firearm</td>
<td>0.113</td>
<td>12.4</td>
<td>0.089</td>
<td>11.9</td>
<td>0.100</td>
<td>17.8</td>
</tr>
<tr>
<td>knife</td>
<td>0.038</td>
<td>23.5</td>
<td>0.078</td>
<td>33.1</td>
<td>0.096</td>
<td>29.2</td>
</tr>
<tr>
<td>Stick</td>
<td>0.412</td>
<td>1.7</td>
<td>0.242</td>
<td>2.2</td>
<td>0.356</td>
<td>2.5</td>
</tr>
<tr>
<td>Threat</td>
<td>0.250</td>
<td>8.4</td>
<td>0.247</td>
<td>14.6</td>
<td>0.376</td>
<td>13.1</td>
</tr>
<tr>
<td>Other</td>
<td>0.129</td>
<td>3.1</td>
<td>0.108</td>
<td>4.9</td>
<td>0.067</td>
<td>4.8</td>
</tr>
<tr>
<td>Total [Inc/Month]</td>
<td>50</td>
<td>68</td>
<td>69</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Prop.S.I shows the proportion of victims that report some injury on each period. For displaying purposes I include a column with the number of incidents per month reported on each weapon-category for each period.
Chapter 3

Crime-Time: The Effect of Ambient Light on Criminal Activity

In this paper we study the effect of ambient light on crime. We take advantages of Daylight Saving Time policy (DST) which imposes exogenous variations in daylight exposure at specific hours of the day. We use a rich administrative database managed by the Chilean national police which is a very centralized agency and collects detailed information regarding each crime incident. We find a significant 20% decrease in property crimes associated to the DST transition that increases in one hour the amount of sunlight for the 7-9pm period. Consistently we find a similar increase in crime when DST transition sharply decreases the daylight exposure for the same period of the day. Our findings are also consistent under two strategies that rely on different identification assumptions: sharp regression discontinuity design and a difference-in-differences regression analysis. We also analyze heterogeneous responses for different crime categories and our results suggest that most of the variation is driven by robbery which decreases 30% during evening hours. Importantly, we detect no significant response induced by DST associated with a particular demand-side response such as the time commuting pattern of the population, and we find no substantial short-term displacement for a particular period of the day.

1Jointly written with Kenzo Asahi, Assistant Professor, School of Government, Pontificia Universidad Catolica - Chile.
CHAPTER 3. CRIME-TIME

3.1 Introduction

Popular wisdom often identifies darkness with criminal activity. You can get that sense from some of Charles Dickens’ novels where a crime usually happens under the so-called cover of darkness. There is also a famous case that involves Abraham Lincoln as a young lawyer where the alleged amount of light was very important. The future President of the United States discredited one of the key testimonies against his defendant showing that the light provided by the moon would not have allowed the witness to identify the murderer from around 100 yards as he had previously declared. In spite of that belief, empirical evaluations documenting this effect are still very scarce. Part of the limitation is due to the fact that comparisons of crime patterns during a day will offer a spurious estimate of this relationship since in the course of the day, ambient light as well as other determinants of crime may spuriously correlate.

In this paper, we present two different approaches to estimate the causal effect of ambient light on crime. Both approaches take advantages of exogenous variations in sunlight due to the implementation of Daylight Saving Time policy (DST hereafter) which is still very common in many countries. First we focus on the sharp variation that DST transition yields in the amount of sunlight exposure at two moments of the day. Under the assumption that other things that may affect crime changes smoothly, a regression discontinuity approach offers a credible estimate of the causal effect. In addition, we take advantage of two exogenous variations in the timing of the DST transition for two particular years which allow us to estimate a causal effect using a more stringent identification strategy. In this case we rely on the fact that the timing of the DST transition is uncorrelated with variations in crime.

We use a rich administrative database provided by the Chilean Government and collected by the Chilean national police (Carabineros de Chile). The main advantage of this database is that it covers the full universe of crimes reported and is collected by a centralized police agency, which is crucial for comparability purposes (e.g. when comparing different years and moments of the day within a large urban area). We have detailed information about each crime incident (day, time, place) for the period 2005-2010 and for the two main Chilean cities: Santiago and Valparaso. The Chilean context might be particularly attractive given its high robbery rate (six times the US robbery rate).

Doleac and Sanders (2015) offers the only available study of the effect of variation in ambient light caused by DST on crime. They use data from the National Incident-Based Reporting System (NIBRS) of 558 United States jurisdictions that covers a total population of approximately 22 million for years 2005-2008. Importantly, most of the jurisdictions covered in the NIBRS survey correspond to low-dense and rural areas. Their research strategy relies on two different sources of variation; different timing when DST policy was imple-

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2 See Henry Fonda and John Ford’s movie Young Mr Lincoln (1939)
3 Van Koppen and Jansen (1999) analyze daily, weekly and seasonal variations of the number of commercial robberies in Netherlands between 1988 and 1994 and find that crime rate is higher in winter than in summer. They attribute that gap to the difference in the number of dark hours during the day but their strategy relies only on OLS analysis using observational data from both summer and winter.
mented for some particular years, and also a RDD using the DST transition to identify sharp variation in sunlight. They focus on felony robbery and other violent crimes such as rape, aggravated assault, and murder. They find a 27% decrease in robbery rate during sunset hour which drives much of the overall 7% decrease after DST transition. They focus only on the spring transition and find no consistent impacts for other crimes. Importantly, they find no significant results for the fall DST transition when ambient light is extended for evening hours, and given they do not have available data for describing variation on victim’s behavior for the population represented in the NIBRS, they interpret they observed effect as the overall effect of DST on crime.

Interestingly, our estimates for two different periods of the year, and implementing two identification strategies are consistent with one another. We focus on the two DST transitions across different years and find similar estimates of crime responses to variation in sunlight exposure. We find a 20% decrease in overall property crime associated to the DST transition that increases in one hour the amount of sunlight for the 7-9pm period. Similarly, we find a 17% increase in crime when DST transition sharply decreases the daylight exposure for the same time of the day. We also analyze specific responses to different types of crime and find large and significant responses for robbery incidents. In the case of robbery, we even detect a significant effect during sunrise hours where overall criminal activity is small.

Our results are consistent under a number of robustness checks. Besides relying on two different identification sources, we analyze the sensitivity of our findings implementing a number of different specifications and falsification tests. First, we find no significant responses for periods of the day when the amount of ambient light does not change because of the DST policy. Similarly, we find no significant responses associated to additional placebo test as false DST transitions across the days of the year. Moreover, our results are robust to the bandwidth definition as well as the level of aggregation of the data (daily or weekly level).

Based on our findings we analyze two additional issues. First, we discuss the degree to which our findings can be driven by a demand-side response. In particular, we focus on victim’s behavior which according to Cook, Ludwig, and McCrary (2011) has been largely neglected in the economics literature (Cook, Ludwig, and McCrary, 2011, p.10). We collected high frequency data from Metro ridership and find that our estimates are robust to the inclusion of information regarding the commuting pattern of the population. Although this piece of information cannot rule out other possible endogenous responses associated with victim or police behavior, the robustness of our results is at least suggestive that they could be mainly driven by potential offender or supply-side responses. In addition, we analyze some possible temporal re-allocations of criminal activity and find no substantial displacement to other periods of the day associated with DST policy.

This paper is organized in seven sections. First, we discuss the theoretical implications of daylight on crime based on two slightly different approaches: the rational choice theory of crime closely associated with the economist Gary Becker in the late 1960s, and the situational crime prevention model closely associated with the work of the criminologist Ronald Clarke in the 1980s. In the fourth and fifth sections we describe the empirical strategies and their
results. The sixth section of extension presents several robustness test of our identification strategy focusing on a different DST transition and estimates for each hour of the day. We also include heterogenous responses estimating several coefficients by each crime category. The seventh section is the conclusion, and we finally offer a rich appendix with tables and figures that complement the basic results of this paper.

3.2 Daylight and Criminal Activity

In this section, we describe two important traditions in criminology relevant to the effect of daylight on crime. First, we discuss the theoretical implications of this effect under the rational choice model developed in the economics of crime literature. This approach offers a theory of criminal behavior based on the incentives faced by different agents in the so-called market for offenses (Becker, 1968). Then, we briefly review the specific insights developed under the situational crime prevention approach which offers an alternative explanation about why ambient light may affect criminal activity.

Daylight and rational choice theory of crime

Rational choice theory has been very influential in criminology since the 1960s after the seminal work of Gary Becker, though it can be traced back to much earlier work on deterrence theory of Beccaria and Bentham. Becker (1968) developed an analytical framework for optimal crime control policy that assumes a specific model for criminal behavior. Becker’s economic approach does not rely on ad hoc concepts such as differential association or anomie to explain criminal behavior; rather, he focused on incentives. He assumed that criminal behavior can be modeled as a choice made by a person whose expected utility exceeds what he could achieve at other activities. In that sense, “persons become criminals, therefore, not because their basic motivations differ from that of other persons, but because their benefits and costs differ” (Becker, 1968, p.176).

Briefly, Becker’s formulation characterizes the decision to commit an offense as a function of three groups of variables: (i) his/her probability of conviction and punishment if convicted; (ii) income available for that person in legal and illegal activities; and (iii) his/her willingness to commit an illegal act. Under this framework, variation in daylight hours may affect the chances that an offender is identified and consequently his or her probability of capture.

Following Becker, we hypothesize that the likelihood of committing a crime will depend on the costs and benefits of offending at a particular time of the day. Thus, offender’s likelihood of committing a crime can be written as follows:

---

4For an overview of the evidence on the deterrent effect of police, imprisonment, and capital punishment see Nagin (2013).

5Since then, many efforts have been made to incorporate other legal and non-legal aspects of crime, such as the feeling of shame and embarrassment as an explicit cost of crime (Williams and Hawkins (1989); Grasmick and Bursik Jr (1990); Hechter and Kanazawa (1997); and, the notion human agency and decision making skills (Cornish and R. V. Clarke, 1987).
\[ P[U(\text{Criminal Activity}) > U(\text{Non-criminal Activity})] = P[B - pC > U_{NC}] \] (3.1)

Where \( B \) represents the benefits of offending, \( p \) the probability of capture, and \( C \) the costs of offending, including all perceived monetary and non-monetary costs associated with offending. We can argue that a sharp variation in the amount of light during a certain period of the day may affect \( B, C \) and \( p \). \( U_{NC} \) represents the net utility of a non-criminal activity available to the potential offender. A reduction in ambient light may reduce the probability of an offender of being identified and then prosecuted which subsequently affects the probability of capture: \( \frac{\partial p}{\partial \text{Light}} > 0 \). In that sense, ambient light may deter criminals from offending.

On the other hand, since \( B \) and \( C \) are determined by all crime opportunities available at a particular time \( h \). We may expect two additional reactions to an increase in ambient light: i. victims may react to the lower perceived risk (as a result of the increase in offender’s probability of capture) by decreasing the level of effort they devote to protect their goods which will decrease the costs of offending \( \frac{\partial C}{\partial \text{Light}} < 0 \), or ii. Increasing the likelihood of circulating with more valuable goods which will increase the benefits of offending either by increasing the loot \( \frac{\partial B}{\partial \text{Light}} > 0 \) or decreasing offender’s costs of searching \( \frac{\partial C}{\partial \text{Light}} < 0 \). In all these cases, offender’s likelihood to offend will increase as a result of an increase in ambient light.

In some way, since we cannot define a priori which effect will be large, the effect of ambient light on crime is an empirical matter. In the final section, we discuss the main implications of these results.

**Daylight and situational crime prevention approach**

R. V. G. Clarke (1997) approach can be seen as an alternative behavioral theory of offending that focuses on crime settings, rather than upon those who commit a criminal act. From a policy perspective, there are many situations where an accurate description of crime settings can be more important than explaining criminal dispositions. In addition, even from a pure rational choice perspective, a situational crime approach might be attractive since decision processes and the factors taken into account are likely to vary greatly at the different stages of decision making and among different crimes (Cornish and R. V. Clarke, 1987, p.933).

Although the discussion about the role of situational factors in crime was originally stimulated by the results of work in correctional treatments in the UK in the 1960s and 1970s ((R. V. Clarke and Cornish, 1985)), its conceptual formulation into a “rational choice
perspective” started in the early 1980s with R. V. Clarke and Cornish (1985). In a sense, the situational crime approach has been influential for crime control purposes, since it directly focuses not only on offenders but also on potential offenders. There are a number of studies of successful applications of situational prevention, and as has been emphasized by R. V. Clarke and Cornish (1985), there are theoretical and practical reasons to support this approach.

From a theoretical point of view, Clarke mainly agrees with Becker’s critique of classical criminological theories. He also argues that crime is mostly explained by people’s choices. However, relative to Beckers classical approach, situational crime prevention incorporates some important innovations to avoid its basic criticisms. Although circumstances surrounding each crime can be seen as part of the three variables identified by Becker that affect individual decisions to commit an offense, Clarke characterizes them more explicitly. He states that a criminal act does not occur only as a result of individual motivation; it also requires two other conditions: a vulnerable target and an appropriate opportunity. This more explicit accounting of situational factors has been crucial for the large influence of this approach on crime research.

In a similar way, Clarke also challenges the idea of a self-maximizing agent who makes decisions based on careful calculations of costs and benefits of every available option. Clarke states that that perspective “does not fit the opportunistic and reckless nature of much crime” (Clarke, 1995). He says that although criminal behavior may involve an important degree of rationality, it is better represented as rudimentary and constrained or bounded by the circumstances. Indeed, he refers to criminal motivation rather than a long-term disposition. According to Clarke, this distinction might be crucial for a broader theory of criminal events, since disposition itself cannot explain why crime occurs at particular time and places. In addition, the idea of motivation may also offer the possibility to incorporate into the theory some deviant behaviors such as impulsive behavior and peer influence that are hard to include under a framework of elaborate calculations of costs and benefits. Thus, the two main elements of this theory of criminal events are: i. a description of the nature and distribution of criminal opportunities; ii. an account of offenders decisions.

In addition, Clarke’s approach has important consequences from a practical point of view. It offers a large scope for action in terms of actual policies that can be implemented to prevent crime. This is particularly important relative to those approaches that almost exclusively focus on the deep causes (social roots) of crime, where the scope for action may be very limited. The situational crime prevention literature is rich in examples where crime was actually reduced by implementing simple solutions. Perhaps the most famous case is

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8See R. V. G. Clarke (1997) for a full description of 16 successful case studies.

9Most crime is the result of deliberate choices made by individuals rather than a product of deep social, economic, and psychological causes (R. V. Clarke, 1983).

10Among others R. V. Clarke (1995) also mentions: i. ignoring rewards that are hard to be translated into monetary terms; ii. treating different crime categories and adding them all as a single variable.

11People choosing to take advantage of naturally arising opportunities or as deliberating creating opportunities; rather than passive actors compelled to behave criminally by deeply rooted causes (R. V. Clarke, 1983).
provided by the unintended effect of the implementation of a mandatory law that required
the use of helmets on motorcycles. After the law was enacted, Mayhew, R. V. Clarke,
and Elliott (1989) report a large decrease in motorcycle theft counteracting a subsequent
increase in other similar crimes, such as vehicle theft. According to them, the response
occurred because few potential thieves have a helmet with them at the opportune time and
place, and without one, they run a high risk of being stopped by the police, preventing them
from committing the crime in the first place.

Ambient light might be a crucial situational factor that affects criminal activity. In
particular, we exploit the variations imposed by daylight saving time transitions, which offer
exogenous shocks on the amount of ambient light for a particular time of the day twice a
year. Under the assumption that the DST transition may affect other things that affect
crime smoothly, we can identify a strategy to analyze the effect of daylight transition on
crime. In the empirical strategy section, we present two alternative approaches that offer
credible causal estimates of this effect under particular assumptions.

3.3 Data Description

Crime reports

We use administrative data from all crime reported to police between 2005 and 2010. Each
crime report contains information about the time and location where the crime was perpet-
uated and it classifies each crime according to 10 different categories. Our analysis is mainly
focused on Santiago, Chile. Santiago has more than 6 million inhabitants. It contains 52
municipalities which represents the basic political administration unit. Crime reports are
collected by Chilean police, which is a very centralized organization (Carabineros de Chile).
They collect detailed information, directly from the victims that includes crime category,
location and time of the incident among other characteristics. Table 3.1 summarizes the
major crimes reported for the years of our analysis. We excluded from the analysis injuries
and domestic violence offenses since they are unlikely to be affected by changes on sunlight
hours.

Sunlight hours and DST transition

We collect information on actual DST implementation for each year in Santiago. We obtained
the precise day of DST implementation for each year based on the 1489 Act records (Decreto
1489). In “normal” years DST transitions occurs after the second Saturday of March (fall
transition) and October (spring transition). In addition, we collected data on exact sunset
and sunrise hours in 2005 where we can observe the sharp variations in terms of sunlight
exposure associated with a particular DST transition during a “normal” year. Figure 3.1

\(^{12}\)Extracted on Feb 2th, 2016 from http://www.tutiempo.net/chile/santiago.html?datos=
calendario#Calendario
Table 3.1: Total crimes by year

<table>
<thead>
<tr>
<th>Year</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Robbery</td>
<td>30,921</td>
<td>33,050</td>
<td>37,948</td>
<td>33,249</td>
<td>31,754</td>
<td>27,983</td>
</tr>
<tr>
<td>Larceny</td>
<td>8,708</td>
<td>9,510</td>
<td>12,335</td>
<td>11,663</td>
<td>12,914</td>
<td>12,445</td>
</tr>
<tr>
<td>Vehicle Theft</td>
<td>7,494</td>
<td>9,357</td>
<td>12,931</td>
<td>13,555</td>
<td>16,837</td>
<td>18,529</td>
</tr>
<tr>
<td>Theft from a Motor vehicle</td>
<td>23,692</td>
<td>20,706</td>
<td>23,848</td>
<td>24,567</td>
<td>27,528</td>
<td>30,902</td>
</tr>
<tr>
<td>Burglary w/people</td>
<td>22,783</td>
<td>21,518</td>
<td>22,308</td>
<td>21,544</td>
<td>21,302</td>
<td>20,104</td>
</tr>
<tr>
<td>Burglary w/o people</td>
<td>10,704</td>
<td>12,672</td>
<td>12,459</td>
<td>12,583</td>
<td>13,074</td>
<td>12,951</td>
</tr>
<tr>
<td>Other Robberies</td>
<td>1,409</td>
<td>3,028</td>
<td>1,921</td>
<td>1,598</td>
<td>1,513</td>
<td>2,282</td>
</tr>
<tr>
<td>Theft</td>
<td>30,523</td>
<td>30,609</td>
<td>33,122</td>
<td>34,337</td>
<td>35,687</td>
<td>36,797</td>
</tr>
<tr>
<td>Murder</td>
<td>131</td>
<td>148</td>
<td>166</td>
<td>123</td>
<td>128</td>
<td>95</td>
</tr>
<tr>
<td>Rape</td>
<td>934</td>
<td>963</td>
<td>919</td>
<td>1,091</td>
<td>1,019</td>
<td>879</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>137,299</td>
<td>141,561</td>
<td>157,957</td>
<td>154,310</td>
<td>161,756</td>
<td>162,967</td>
</tr>
</tbody>
</table>

Source: Carabineros de Chile, Subsecretaria del Delito, Ministerio del Interior, Chile.

shows the daily evolution of sunset (blue line) and sunrise hours (red line) in 2005.

Importantly, we found two exceptional episodes in 2008 and 2010 DST when March transition was delayed for three weeks due to natural causes: the 2008 drought and the 8.8 Richter scale earthquake (2/27/2010) that largely affected the central part of the country. In the empirical strategies section we discuss these two exceptions which are crucial to one of our identification strategies.

### 3.4 Empirical Analysis

The empirical challenge of this paper is to analyze the relationship between daylight exposure and criminal activity. As we discussed earlier, the main problem is that it is hard to disentangle the extent to which sunlight modifies peoples behavior in terms of their decision and activities which may affect the opportunities for crime and the behavior of potential offenders. Rather than an attempt for a complete description of the criminal behavior where sunlight exposure may be an important factor, we rely on two exogenous variations that offer an opportunity to empirically estimate the causal effect. Given the data we have available we are able to estimate this effect for different situations. In particular, we estimate the effect of DST transition on crime for different moments of the day and in two different periods of the year. In addition, we offer a complementary identification strategy which also relies on exogenous variation on ambient light across the calendar year.

First we describe a regression discontinuity design that takes advantages of the sharp variation in daylight exposure that DST transition produces around sunrise and sunset hours. We use this approach to test whether an increase/reduction on daylight exposure causes a
Notes: Red and blue lines represent respectively the exact sunset and sunrise times for each day of the year. Source: Astronomical information extracted on February 2th, 2016 from http://www.tutiempo.net/chile/santiago.html?datos=calendario#Calendario

reduction/increase on crime when looking at the two DST transitions of each year. We complement that approach implementing a second identification strategy which relies on a different source of variation due to an exogenous delay on the DST transition that occurred during the period for which the data is available. As we mentioned before, in 2008 and 2010 the Government decided to delay the fall transition (March) three weeks. We believe that this exogenous variation offers another research opportunity to analyze the effect of daylight on crime. In this section we describe the details of each approach.

**Sharp Regression Discontinuity Design**

The potential outcomes framework or the so called Neyman-Rubin causal model (Sekhon, 2008) offers a simple way to specify why under certain circumstances a regression discontinuity design yields a causal estimate of a particular effect (Imbens and Lemieux, 2008). Its basic identification assumption is that the conditional expectation functions of potential outcomes are continuous in the vicinity of a certain cutoff. Our dependent variable $Y_i$ represents the amount of criminal activity observed during a particular period of the day and
$X_i$ is some temporal measure that indicates proximity to DST transition. Formally, we can write that:

$$E[Y_i(0)|X_i = x] \text{ and } E[Y_i(1)|X_i = x] \text{ are continuous in } x \quad (3.2)$$

Thus, we can estimate the average treatment effect $\rho$ around a certain point $c$ as follows:

$$\rho = \lim_{x \to c^+} E[Y_i|X_i = x] - \lim_{x \to c^-} E[Y_i|X_i = x] = E[Y_i(1) - Y_i(0)|X_i = c] \quad (3.3)$$

In our case we implement this strategy for causal inference since we know the exact rule that describe the treatment assignment which in this case is determined by the time-schedule imposed by Daylight Saving Time policy. The continuity assumption requires smoothness in a small neighborhood of the DST transition, so any discontinuity of the conditional distribution of the outcome at the threshold value can be interpreted as evidence of a causal effect (Imbens and Lemieux, 2008). In this case the treatment can be defined as a sharp variation of daylight exposure which is precisely determined by the DST transition. In particular, we focus on the one-hour variation imposed by DST transition twice a year. In terms of sunlight exposure, for each DST transition there are two moments of the day that are highly exposed to this source of variation; and we call them sunset (19:00-20:59) and sunrise (6:00 - 7:59) hours. There is no reason to believe that other moments of the day (nighttime and daytime) are exposed to this particular treatment during that same period. Following Angrist and Pischke (2008) we propose a simple model whose specification directly estimates the causal effect of DST transition on crime at the period of the day $h$, so we run several regressions depending on the period of the day ($h$) we focus on $^{13}$:

$$\log(\text{Crime}_{i,t,h}) = \alpha_h + \beta_{1,h}X_{i,t,h} + \beta_{2,h}DST_{i,t,h}X_{i,t,h} + \rho_hDST_{i,t,h}X_{i,t,h} + \omega_{i,h} + \psi_{t,h} + \epsilon_{i,t,h} \quad (3.4)$$

The dependent variable $\log(\text{Crime}_{i,t,h})$ measures the log of total crimes for a particular day $i$, year $t$, during the daytime period $h$. The running variable $X_{i,t,h}$ indicates the number of days before and after the DST transition and is centered to zero meaning the day when the DST transition actually occurred for each particular year $t$. $DST_{i,t,h}$ is an indicator function of whether a day $i$ in year $t$ was exposed to the DST transition or not, and we also include an interaction term $DST_{i,t,h} \times X_{i,t,h}$ to control for any change in slope at each side of the threshold. In order to have a more flexible function we also consider additional functional forms such as a quadratic specification of the running variable $X_{i,t}^2$, and an interacted term $DST_{i,t,h} \times X_{i,t,h}^2$. We also include $\omega_{i,h}$ (day of the week) and $\psi_{t,h}$ (year fixed effects) to better

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$^{13}$We also try several functional forms specifications including other functional form for the running variable and a lowess regression function. We also run a model excluding weekends day which shows a different pattern in terms of crime variation. Finally, we also collapse the data at the municipal level and run a linear probability model for the probability of a crime during a certain period of the day. Across all those specifications the results were fundamentally the same and some of them can be found in the appendix.
approximate the cyclical structure of crimes, and finally $\epsilon_{i,t,h}$ represents the idiosyncratic error term. The parameter $\rho_h$ is our coefficient of interest which captures the effect of sunlight variation on the percentage of total crimes during a particular period of the day defined by $h$.

**Difference-in-differences approach**

As a complementary analysis, we also estimate the effect of this sharp variation in daylight exposure under a second identification strategy. Here we exploit another source of exogenous variation, namely a delay in the DST transition. In particular, we take advantages of the fact that for two particular years the Chilean Government decided to delay the DST fall transition which by law must occur after the second Saturday of March. Under the assumption that this decision was orthogonal to our dependent variable we can build a natural counterfactual for our treatment group determined by those years where the DST fall transition was implemented as the law regularly establishes it.

A reasonable concern of the RD identification strategy may raise the issue that crime incidence may also be affected by the period of the year itself. This can be particularly relevant for the estimates based on the fall season (DST transition in March). In Chile, March is the first regular month of the year for the basic activities of the population. The academic year for all school levels as well as many job start regularly during the first two weeks of March, right after the end of vacation period during January and February. If people are learning how to accommodate to their schedules during these two weeks of March, the difference between these two weeks and the following two may capture more than simply the effect of DST schedule. In that sense, the RD estimates might be biased.

The difference-in-differences strategy precisely offers a robustness check for this concern since it relies on the timing where this exogenous variation happens for two specific years. In particular, Act 1498 establishes that March transition must be implemented after the second Saturday of March each year. However, in 2008, due to a hard drought the government decided to delay by three weeks the implementation of the winter-time with the hope of reducing the energy consumption. Similarly, in 2010, after the strong earthquake, the government also decided to postpone by three weeks the implementation of the winter-time in order to help families, volunteer and organization groups that were working on the first steps of the reconstruction process and taking full advantages of sunlight hours in the evenings. Figure 3.2 illustrates the variation in terms of the sunrise and sunset hours across days of the year.

We follow Doleac and Sanders (2015) taking advantages of the variation in the day of the year where the DST transition was implemented and the variation in the impact of DST across different hours of the day. For this case, we restrict the sample to the earliest DST transition in March for the treatment years (after Saturday 8th in 2005) and for the control years (after Saturday 29th in 2008). We collapse all the data to day-by-sunset level, where sunset represents a two-hour period when sunset-time actually happened for that year. Our basic regression can be described as follows:
CHAPTER 3. CRIME-TIME

Figure 3.2: Sunrise and sunset hours in 2005. Fall DST transition delay

\[ \log(\text{Crime}_{i,t}) = \alpha + \beta_1 T_{\text{Treat},i,t} + \beta_2 \text{Sunset}_{i,t} + \gamma T_{\text{Treat},i,t} \times \text{Sunset}_{i,t} + \epsilon_{i,t,h} \]  

where represents the log of total crimes in a particular day-hour period. indicates whether observation \( i \) corresponds to years where regular DST transition was implemented (2005, 2006, 2007, 2009), as opposed to the control years which are 2008 and 2010. In other words, we can interpret as a treatment group specific effect that accounts for average permanent differences between treatment and control groups. indicates whether observation \( i \) corresponds to sunset-hours, as opposed to the rest of the hours of the day, so it enters this model as a common-trend effect for treatment and control groups as is usual in difference-in-differences specifications. represents in this case our parameter of interest; it captures the double difference between treatment and control groups and sunset-hours versus the rest of the day-hours.

Notes: Red and green lines represent respectively the exact sunset and sunrise times for each day of the year. Source: Astronomical information extracted on February 2th, 2016 from [http://www.tutiempo.net/chile/santiago.html?datos=calendario#Calendario](http://www.tutiempo.net/chile/santiago.html?datos=calendario#Calendario)
3.5 Results

The main results of this project are presented in three parts. First, we present a set of stylized facts comparing the distribution of criminal activity across hours of the day for a short period of time before and after DST transition. Then, we move to RD estimations beginning with a graphical representation for our preferred RD estimate. We present regressions coefficient under different model specifications. The last part of this section shows the diff-in-diff estimates. For the first two parts, the results are based on the spring DST transition during sunset hours since this transition incorporates the most stable bandwidth. Results for the rest of the moments of the day and periods of the year are fully reported in the extension section and the Appendix.

Graphical Analysis

The first feature of crime distribution over time that we want to highlight is its large variation over time during an average day. Figure 3.3 plots a histogram of crime distribution over hours of the day for two different periods: three weeks before (winter) and three weeks after (summer) DST transition. For the two periods the distribution of crime incidents is very similar and shows a general pattern with a small proportion of incidents during nighttime hours (24 to 6AM), followed by a period of an increasing rate until 1PM. After 1PM the rate of incidents remain stable until 6PM. Between 7PM and 9PM is the period with the highest crime rate. If the variation in light is affecting the criminal activity we may expect to see an important variation during these hours of the day. Indeed, we observe a sharp reduction on crime incidents precisely around 7PM and 8PM which can be associated to the implementation of a new time schedule. Figure 3.13 in the Appendix section shows the same pattern for the Fall (March) DST transition. In addition you can find similar histograms for each year and DST transition in Figures 3.14 and 3.15. Finally, also in the appendix section you can Figures 3.16 and 3.17 with histograms but modifying the window period for summer and winter seasons.

Our primary focus is the discontinuity associated in the vicinity of sunset hours. Similarly, we may expect variations around the period of the day that includes sunrise hours. In addition, analyzing similar responses for other periods of the day that are not affected by variations in ambient light are also relevant. Based on that idea, we define four relevant periods of analysis: Nighttime hours (9:00PM to 5:59AM), Daytime hours (10AM to 5:59PM), Sunset hours (7:00PM to 8:59PM), and Sunrise hours (6:00AM to 7:59AM). Figure 3.4 plots the residuals from a regression that adjust for the variation of crime incidents relative to the day when DST transition occurred for sunset hours. Similar plots for night, day, and sunrise hours can be found in Figures 3.18- 3.22 in the Appendix. We include six different figures that show the discontinuity associated with DST at sunset hours but not at other hours of the day. For graphical purposes, and given the cyclical pattern of criminal activity, in Figure 3.4 we plot the residuals of a regression that control for year and day of the week effects.
Figure 3.3: Distribution of crime reports by hour of the day. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Figure represents a histogram of crime reports by hours of the day. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which always occurred after the second Saturday of October. Sample in this case includes a window of three weeks after (summer) and before (winter) the DST transition in October. Source: Own elaboration.

We interpret the sharp discontinuity at the threshold in Figure 3.4 as the effect of ambient light on criminal activity. Interestingly, similar results for other different periods of the day (see Figures 3.18-3.22 in the Appendix) do not suggest a clear association with DST transition. Figure 3.4 suggests a 20% reduction on crime incidents. In October, DST transition implies that sunset-hours (7PM to 9PM) increase by one hour the sunlight period. In order to make clear that point we should consider that on Saturday 10/8/2005 sunset was at 18:49 while the immediate following day (after the DST transition) on Sunday 11/8/2005, sunset was at 19:49. Conversely, during sunrise hours we experience a sharp decrease of one hour of sunlight for the same transition.

In the appendix, we include similar results exploiting the variation in ambient light due to the March DST transition. Interestingly, we find similar results in magnitude but with the opposite sign. We interpret this finding as consistent with the fact that variation in ambient light is directly affecting the amount of criminal activity observed in the urban space. As
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Figure 3.4: Linear adjustment of residuals of log crime estimated at each side of the threshold at Sunset hours. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Each figure corresponds to adjustments at each side of the threshold at sunset hours using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the same is restricted to 21 days at both sides of the threshold. Similar figures for others daytime periods and using different adjustment of the running variable and its interaction with the treatment variable are in the Appendix section (Figures 3.18-3.22). Source: Own elaboration.

in Figure 3.4, Figure 3.23 in the Appendix plots the linear fit of the residuals at each side of the threshold. In addition, Figures 3.24-3.28 displays in different ways the discontinuity around a threshold defined by DST transition for the four periods of the day.

Basic Estimates

RD Estimates: Spring DST transition - October

Table 3.2 shows the results for our variable of interest which is the start of summer season based on the DST transition in October. We can see under different functional specifications a reduction of 20% that can be attributed to the extra hour of sunlight during that period. Similar results for the other relevant periods of the day are shown in the Appendix Table
3.5. Interestingly, we do not see significant variation that can be attributed to the new time-schedule during other day periods. Perhaps the most striking result is that we do not see any effect during sunrise hours which are also affected by a sharp variation on sunlight hours.

Table 3.2: RD estimates of the DST transition: Sunset hours.
All crimes: Santiago 2005-2010 around Spring DST transition (October)

<table>
<thead>
<tr>
<th></th>
<th>Sunset</th>
<th>Sunset</th>
<th>Sunset</th>
<th>Sunset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Summer (D)</td>
<td>-0.259***</td>
<td>-0.205***</td>
<td>-0.205***</td>
<td>-0.173</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Days</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Days2</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Summer*Days</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Summer*Days2</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>DoWeek FE</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td>210</td>
<td>210</td>
<td>210</td>
<td>210</td>
</tr>
<tr>
<td>R2</td>
<td>0.027</td>
<td>0.092</td>
<td>0.141</td>
<td>0.141</td>
</tr>
</tbody>
</table>

Notes: Regressions consider log of crime incidents as the dependent variable and it includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which always occurred after the second Saturday of October. The sample in this case includes a window 17 days after (summer) and before (winter) the DST transition in October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Results in Table 3.2 seem to be very robust to the window definition. In the following section, Figure 3.9, we show the estimates of summer coefficient for each daytime period where we find no effect on crime.
CHAPTER 3. CRIME-TIME

RD Estimates: Fall DST transition - March

We reproduce our previous RD estimates using the DST fall transition which imposes variations in ambient light in similar hours of the day but in the opposite direction. Interestingly, we find a consistent increase in crime during sunset hours which coincides with a sharp decrease in ambient light during that hour of the day. Again, we find no significant crime variation associated with other periods of the day. Table 3.3 shows the results for the DST transition in fall during sunset hours. Since this transition is from summer to winter we called our relevant independent variable as winter.

Table 3.3: RD estimates of the DST transition: Sunset hours All crimes: Santiago 2005-2010 around Fall DST transition (March)

<table>
<thead>
<tr>
<th></th>
<th>Sunset</th>
<th>Sunset</th>
<th>Sunset</th>
<th>Sunset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td>0.185** (0.08)</td>
<td>0.185*** (0.07)</td>
<td>0.170** (0.07)</td>
<td>0.236** (0.11)</td>
</tr>
<tr>
<td>Days</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Days2</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Summer*Days</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Summer*Days2</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>DoWeek FE</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>221</td>
<td>221</td>
<td>221</td>
<td>221</td>
</tr>
<tr>
<td>R2</td>
<td>0.059</td>
<td>0.236</td>
<td>0.253</td>
<td>0.256</td>
</tr>
</tbody>
</table>

Notes: Regressions consider log of crime incidents as the dependent variable and includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which usually occurred after the second Saturday of March. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Again, we find no significant effect on crime for other periods of the day. Different coefficients can be compared in the Appendix Table 3.6. In addition, these results seem to be robust to the window definition which is displayed in Figure 3.34 in the Appendix section.

Although the similarity of the results can clearly be presented as a robustness check, we believe that regarding this particular DST transition a possible caveat should be taken into account. In Chile, March is the first regular month of the year for the basic activities of the population. Academic year at all school levels and job starts regularly during the first week of March. That particular feature of March may affect our estimation which relies on variation of stable patterns for crime activities at each side of the threshold. DST March transitions
usually occur after the second Saturday of March. However, as we have mentioned earlier, there are two years where the DST implementation was delayed substantially. In 2008, due to a hard drought the government decided to delay the implementation of the winter-time with the hope of reducing energy consumption. Similarly, in 2010, after the strong earthquake, the government also decided to postpone the implementation of the winter-time in order to help volunteer and organization groups that were assisting people in need to take full advantage of sunlight hours. Thus, since our RD estimates are calculated using the actual DST transition dates, we believe they likely reflect the effect of ambient light on crime imposed by this policy.

**Difference-in-differences Estimates: Fall DST transition - March**

Our difference-in-differences estimates captures the double difference between years where the DST transition was implemented as customarily, and the years when there were a delay of three weeks, but also controlling for the difference between sunset-hours and the rest of the day. Under the assumption of common-trend between these two groups of years we can interpret our estimate as the causal effect of a variation in daylight exposure on crime. It is important to keep in mind that this particular source of variation is available only for the fall DST transition which usually occurs in March. During this DST transition, sunlight period decreases sharply during sunset hours. Conversely, during sunrise hours we experience a sharp increase of one extra hour of sunlight.

As we mentioned earlier, we collapsed the data to day-by-sunset level, where sunset represents a two-hour period when sunset-time actually happened for that year. In addition we repeated that procedure considering as sunset-hours or the relevant period each hour of the day which directly offer a falsification test for the effect of daylight variation on crime. Figure 3.5 summarizes all those estimates with their respective confidence intervals.

As we can see in Figure 3.5, it is very clear that we see no significant effect except for the estimates that are based on the real sunset-hours. These estimates represent a 15% increase in crime which is slightly smaller in absolute value than our previous RD specification based on the spring DST transition (18% decrease), but much similar to our RD estimate based on the same fall DST transition (17% increase). Interestingly, we estimated the same diff-in-diff model for the city of Valparaiso and we found very similar values. See Figure 3.36 in the Appendix.

**Robustness and Falsification Tests**

So far, we have interpreted our results as the effect of ambient light on crime, and we have not detected any significant effect for periods of the day that where DST does not induce a sharp variation in ambient light. The fact that we detect no effect for the periods of the day that do not experienced variation in ambient light induced by DST policy can be offered as a basic robustness check. As a stylized fact, we can analyze Figure 3.6 which resembles the previous histograms but considering a false DST transition that would have happened after
CHAPTER 3. CRIME-TIME

Figure 3.5: Difference-in-differences estimates by hour of the day. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Notes: Figure represents hourly estimates of 24 diff-in-diff regressions. Each regression is estimated using a two-hour window period and the coefficient is plotted at the initial hour of the period. The dependent variable is log of crime incidents and includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which usually occurred after the second Saturday of March, except for the years 2008 (March 29th) and 2010 (April 4th) which are used in this case as controls. The sample in this case is restricted to the period between the earliest DST March transition between the treatment (March 8th) and control groups (March 29th).

the second Saturday of May. In this case, no sharp variation in criminal activity is observed for the three weeks before and after the false DST transition. In the appendix, Figures 3.29 and 3.30 show similar results for other months of the year. No important variations are related to any of those false DST transitions.

As a general falsification test that analyze the effect at sunset hours we present Figure 3.7. The dashed line represents our coefficient for our true DST transition. In the appendix, Figure 3.31 shows similar result for robbery incidents. In both cases we have that our "true coefficient" represents a singular value on the distribution of the possible "treatment" variables across the days of the year.

Another possible concern could be related to specific variations associated to the first group of days after the DST transition. We discuss the robustness of our results in Figures
CHAPTER 3. CRIME-TIME

Figure 3.6: Distribution of crime reports by hour of the day. All crimes: Santiago 2005-2010 around False DST transition (May)

Notes: Figure represents a histogram of crime reports by hours of the day. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to a false DST schedule which is assumed to happen after the second Saturday of May. Sample in this case includes a window of three weeks after (summer) and before (winter) the DST transition in October. Source: Own elaboration.

3.8 and 3.9. Figure 3.8 shows graphically the results from a RDD comparing the amount of crime observed at the weekly level. Part of the variation in criminal activity that is related to the day of the week pattern goes away since we are collapsing every point at the week level. Again, the results are consistent in terms of the basic pattern for every period of the day and the magnitude of the coefficient at sunset hours. Again, no significant effects are found at other moments of the day.

Finally, Figure 3.9 shows how robust to the bandwidth size are the coefficients we have presented. Again, we observe only consistent coefficients at sunset hours. Estimates using more flexible functional forms as well as a similar figure for the March DST transition can be found in the Appendix, Figures 3.32-3.34.
Figure 3.7: Histogram of RD estimates by Day of the Year. All Crimes: Santiago 2005-2010 around Sunset hours

Notes: Figure represents a histogram of RD coefficients estimates using equation (1) for every day of the year. We exclude the days after December 15th and before April 15th to avoid both strong seasonality effects associated with summer and DST Fall transition. In all regressions sample includes a window of three weeks after (summer) and before (winter) the false DST transition. Dashed line represents the value of our true DST transition in Spring. Source: Own elaboration.
Figure 3.8: Fractional polynomial adjustment of log crime estimated at each side of the threshold by daytime hours. All crimes: Santiago 2005-2010 around Spring DST transition (October).

Notes: Each figure corresponds to adjustments at each side of the threshold using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the sample is restricted to 11 and 7 weeks before and after the threshold. Source: Own elaboration using AUPOL.
Figure 3.9: RD coefficients sensitivity to days at each side of the threshold by daytime period. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Each figure corresponds to adjustments at each side of the threshold using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the sample is restricted to 11 and 7 weeks before and after the threshold. Source: Own elaboration.
Further Results

In order to analyze variations in criminal activity associated with DST policy in a more general way, we present different estimates by hour of the day. By doing this exercise we confirm our previous results that most of the crime variation is associated with those periods of the day that are affected by variations in ambient light imposed by DST policy. Finally, we extend our results by distinguishing effects by specific types of offense. We find that robbery is by far the most responsive crime to the changes in ambient light imposed by the DST policy. Although we cannot fully rule out the importance of ambient light for other types of crime we discuss why in this particular case we are able to detect a clear effect in robbery.

Sensitivity to Hours using Spring Transition

A natural generalization of our aggregate results for different hours of the day that we discuss in Table 3.2 and Table 3.5 is presented in Figure 3.10. We estimate 24 separate estimates by each hour of the day.

As we can see in Fig 3.10 the largest variation in criminal activity is associated with sunset hours (7PM and 8PM) when we see a 20% decrease. Although some noisy estimates during the rest of the day we find no consistent pattern that can be associated with the variation in ambient light. Interestingly, we find a positive but not significant effect at 6AM that suggest an increase in crime that could be related to a reduction in ambient light during that period of the day.

Heterogenous responses by crime type: Spring DST transition

Table 3.4 we present separate estimates for each crime category and period of the day. Although all crime categories we have analyzed in this article can be grouped as property crimes, we believe that some important features of each of them should be taken into account. Perhaps the most crucial distinction for the purposes of our identification strategy has to do with the accuracy of the reported time of each crime category. Since we are using reports that are mostly done by victims, how accurate is the time reported is influenced by the type of offense he/she suffered. For instance, a victim can clearly recall the time when he/she was robbed while in the case of burglary without people he/she needs to make an estimation based on some basic facts (last time he/she was there, when he/she noticed the incident, etc). A similar claim can be made for the rest of crime categories identified in the sample.

At a first glance, almost all estimates are not significant except for the case of robbery. We believe that robbery is likely driving our previous estimates when we pool all crime categories together; especially considering both its high incidence in the overall crime category and its sensitivity to different each time period. Indeed, for the case of robbery we find an even larger response in sunset hours (33% decrease), and also, we find a similar response in the opposite direction (32% increase) during sunset hours. In the Appendix section we complement this analysis with three additional tables. First, in Table 3.7 we reproduce Table 3.4 estimates
### Table 3.4: RD estimates of summer by Offenses and daytime periods during DST transition. Santiago 2005-2010 around October DST transition (spring)

<table>
<thead>
<tr>
<th></th>
<th>Night</th>
<th>Day</th>
<th>Sunset</th>
<th>Sunrise</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Crimes</td>
<td>0.059</td>
<td>-0.081</td>
<td>-0.205*</td>
<td>0.0154</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.06)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Robbery</td>
<td>0.0693</td>
<td>-0.128</td>
<td>-0.334*</td>
<td>0.318*</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.07)</td>
<td>(0.10)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Larceny</td>
<td>0.0501</td>
<td>-0.236**</td>
<td>0.084</td>
<td>0.0704</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.09)</td>
<td>(0.13)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Vehicle Theft</td>
<td>0.093</td>
<td>-0.118</td>
<td>-0.203</td>
<td>-0.0301</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.08)</td>
<td>(0.14)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Theft from vehicles</td>
<td>0.126</td>
<td>-0.0546</td>
<td>-0.263</td>
<td>-0.182</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.16)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Burglary w/People</td>
<td>-0.0618</td>
<td>0.0405</td>
<td>-0.309*</td>
<td>-0.277</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.06)</td>
<td>(0.14)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Burglary w/o People</td>
<td>0.0197</td>
<td>0.0428</td>
<td>-0.169</td>
<td>0.0207</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.08)</td>
<td>(0.17)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>Other robbery</td>
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<td>-0.151</td>
<td>-0.0382</td>
<td>-0.253</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.17)</td>
<td>(0.19)</td>
<td>(0.19)</td>
</tr>
<tr>
<td>Theft</td>
<td>0.0463</td>
<td>-0.124</td>
<td>-0.184</td>
<td>-0.0924</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.07)</td>
<td>(0.10)</td>
<td>(0.18)</td>
</tr>
</tbody>
</table>

Notes: This Table contains estimates from 36 regressions. Each regression considers log of crime incidents as dependent variable and includes all crimes reported excluding injuries and domestic violence incidents. Summer refers to the DST schedule which always occurred after the second Saturday of October. All estimates are calculated using the same regression which includes the running variable (days), an interaction term between days and summer, day of the week fixed effects and year fixed effects. Sample is also restricted to include 17 days before and after the DST transition in October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Figure 3.10: RD estimates of summer by Hour. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Each point represents the RD estimate of a regression using a sample restricted to the hour indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable and it includes all crimes reported excluding injuries and domestic violence incidents. Summer refers to the DST schedule which always occurred after the second Saturday of October. All estimates are calculated using the same regression which includes the running variable (days), an interaction term between days and summer, day of the week fixed effects and year fixed effects. The sample is also restricted to include 17 days before and after the DST transition in October.

for the fall DST transition, and we detect a significant response (30% increase) for robbery during sunset hours which is consistent with the sharp decrease in ambient light of that particular DST transition. We also find no clear pattern associated with the rest of crime categories. In addition, we include Tables 3.8 and 3.9 which contain hourly estimates by each crime category. While these estimates are presumably much noisier we still find significant effects on criminal activity associated with robbery during sunset hours separately for both DST transitions.
3.6 Extensions

We discussed two additional features of our findings. First, we analyze the extent to which our findings are driven by demand-side responses which in this case refers to victim’s behavior. As we have discussed earlier, our results are reduced-form estimates of the effect of ambient light on crime without differentiating supply or demand-side responses induced by DST. We incorporate a simple measure of victim’s behavior such as the daily time-commuting pattern and measure the extent to which this variable is also affected by the DST variation. A substantial response in terms of time-commuting pattern will unable us to distinguish a supply from a demand-side response. In addition, we evaluate whether it substantially alter our reduced-form estimates when incorporating on our main estimation as a covariate. In either case we find no significant response associated with the commuting-pattern of the population. In addition, we carefully analyze our results to discuss the degree to which they may be indicative of some temporal reallocation of criminal activity that may suggest evidence of temporal displacement in a very short-term scale.

Evaluating a response in the commuting pattern of the population

Most of the empirical studies in economics of crime take victims’ behavior ass given. However, victims can affect the criminal activity through different ways, especially by altering their own level of risk. Victims can avoid circulating certain areas or at a particular time of the day, hardening a particular target or simply opposing a higher level of resistance when attacked. Ideally, we may incorporate to our estimation a full specification of victim’s behavior for every hour of the day. An interesting piece of information that is available about them is their commuting pattern. Considering that most of the criminal activity occur when people return back to home in the evening, we analyze the extent to which our estimates are driven by a variation on victims’ behavior. We run the following regression for every hour of the day.

\[
\log(M_{i,t,h}) = \alpha_h + \beta_{1,h}X_{i,t,h} + \beta_{2,h}DST_{i,t,h} + \rho_hDST_{i,t,h} + \omega_{i,h} + \psi_{i,h} + \epsilon_{i,t,h} \quad (3.6)
\]

We use Metro ridership data which is one of the most important transportation mode of the population in Santiago, Chile. In 2010 Metro had 108 stations with a total network of approx. 100 km. It transports 2.5MM passengers per day which represents around 14% of all total trips in an average day. We collected the number of people who entered Metro system for every hour during the same period for which our crime data is available. In particular, \(M_{i,t,h}\) represents the number of people who entered the Metro system in hour \(h\), day \(i\) year \(t\). Controls also include year and day of the week fixed effects as in equation (3.4).

Results from regression 3.6 are displayed in Appendix Tables 3.10 and 3.11. We find no significant variation associated with the variation in ambient light which suggest that at least

\(^{14}\text{See Domínguez (2017) for a more detailed discussion about this issue}\)
our results are not fully driven by a change in the commuting pattern of the population. In a way, this finding contrasts with Wolff and Makino (2012) who evaluate the effect of DST policy on people’s time allocation problems using American Time Use Survey (ATUS). They find modest variation associated with DST when evening hours become lighter: people declare to spend 3% more of their time towards outdoor recreational activities and reduce TV watching by 9 minutes.

**Evaluating possible temporal reallocation of criminal activity**

We also discuss possible scenarios of short term displacement. Evidence of displacement is crucial in the economics of crime literature, and it may substantially affect the evaluation of a particular policy. An interesting case in this regard is offered by Jacob, Lefgren, and Moretti (2007). They found substantial displacement exploiting weather shocks that significantly alter the amount of criminal activity across US cities. They present a dynamic model and show that for a larger period of time (across different weeks) displacement is consistent with wage fluctuations with a meaningful income effect that persists across periods.\(^{15}\)

We analyze the extent to which DST transition is associated with temporal displacement of the criminal activity in a much smaller period of time across hours of the day within a certain day or week. In the previous section, we showed no significant responses in terms of criminal activity for other hours or periods of the day when arguably the amount of light did not change with DST transition. In a way, the fact that most of our estimates associated with periods of the day without substantial variation in ambient light can be indicative of no temporal displacement across hours of the day induced by the DST policy. In this section, we discuss this finding in more detail.

If no temporal displacement occurs we can expect that overall variation induced by DST transition is strongly influenced by the effect at sunset hours where most of the criminal activity happens during the day. Thus, RD estimates using 3.4 with overall daily crime incidents as dependent variable should yield a variation in the number of crime with the same sign and similar in magnitude as the one suggested by the estimates at sunset hours. We show those results in the Appendix where most daily estimates are not significant but consistent with the variation observed at sunset hours.

Figure 3.11 puts together two sets of data. It compares the distribution of criminal activity for two crime categories: all property crimes (left) and only robbery (right). Top figures show the criminal activity for every hour of the day for two periods before and after Spring DST transition; bottom figures show the difference in criminal activity between those two same periods at every hour of the day.

Similar to the set of histograms we presented in section 5.b. we see that the largest variation occurs at sunset hours, but there are some positive variations at other hours of the day. A preliminary test for short-term temporal displacement can simply compare the

\(^{15}\)On the other hand, they argue that no temporal displacement is consistent with complete myopia or inability to save and borrow.
Figure 3.11: Crime differences across hours of the day. Property Crimes and Robbery during Spring DST transition

Notes: Figure shows distribution of incidents across hours of the day between three weeks before (winter) and after (summer) Spring DST transition. Figures at the left are built using a sample that pools all property crimes together whereas figures at the right refer to robbery incidents. Top panels illustrate differences in terms of number of incidents whereas panels at the bottom describe the difference between summer and winter incidents for every hour of the day. Summer refers to the DST schedule which always occurred after the second Saturday of October.

variation in criminal activity across hours of the day. The overall daily observed variation in incidents is -2.5% and -0.3% for property crime and robbery, respectively. Again, we test for overall crime variation using specification 3.4 and find for both property crime and robbery incidents a small and no significant decrease that can be attributed to the DST policy. Figures 3.37, 3.38 and 3.39 in the Appendix show coefficients for overall daily estimates using both October and March DST transitions.

Interestingly, in the case of property crimes, overall daily variation is similar in magnitude to the variation experienced at sunset hours and we also find no significant variation at sunset hours. These two facts suggest that the overall observed differences are driven by what occurs during sunset hours. However, for the case of robbery, the overall daily variation is lower in magnitude than the difference observed at sunset hours which might be indicative of some sort of displacement across hours of the day. In the appendix, we show similar estimations
for the case of Winter DST transition which yields consistent results.

Although our estimates from Tables 3.4, 3.8, 3.9, and Figure 3.10 suggest that substantial displacement across all hours of the day is not detected, an alternative test might be looking at a particular period of the day where displacement is more likely to happen. If criminals set a target of money to be collected in a day in the spirit of NY taxi cabs of Camerer et al. (1997), we may expect that a sharp reduction in criminal activity at sunset hours may incentivize them to increase their efforts during the following period (e.g. night hours before midnight). We test for the presence of substantial displacement for this period of the day.

Figure 3.12 shows bandwidth sensitivity of RD estimates using both property crimes (left) and robbery incidents (right) as dependent variable. We restricted the analysis for the period 21-23 hrs. Most coefficients for property crimes are positive but none of them significant. Interestingly, robbery coefficients are slightly larger, and indeed for a specific bandwidth size we detect a positive increase which might be indicative of displacement to later hours during a day. However, it is important to keep in mind that even in the case of that particular coefficient (bandwidth 30 days), the total return in terms of crime reduction at sunset hours (-5.76%) exceeds the eventual increase at later hours (+4%).
Figure 3.12: RD coefficients sensitivity to bandwidth size: 21-23 hrs Property crimes (Left) and Robbery incidents (Right): Santiago 2005-2010 around Spring DST transition

Notes: Figures show RD estimates using different bandwidth sizes using equation (1). Sample is restricted to the period 21-23hrs, right after sunset hours. Left and right figures show estimates for property crime and robbery respectively. All coefficients are estimates for Spring using days before (winter) and after (summer) Spring DST transition.
3.7 Conclusion

In this article, we present evidence regarding the causal effect of ambient light on criminal activity. We find a consistent effect of ambient light on the amount of criminal activity reported to the police. In particular, we find that a one-hour increase (reduction) in the amount of light at sunset hours (between 7-8:59 PM) reduces (increases) the amount of criminal activity by 20%. Interestingly, for the rest of the day, our preliminary results show no significant or consistent pattern.

Our results are robust to a variety of model specifications and tests. First, we take advantage of sharp variations on ambient light imposed by DST policy and implement a regression discontinuity research design. We find significant variation only at those hours of the day that are substantially affected by variations in ambient light (sunset hours). In addition, we find a consistent effect on criminal activity associated with different DST transitions. Indeed, we find an increase in crime when ambient light is abruptly reduced, and similarly, we find a reduction when ambient light increases. Interestingly, our two estimates for those two transitions are similar in absolute value. Similarly, these results are robust to a variety of tests, namely different functional forms and sample sizes.

We also complement our findings with a second research strategy that confirms the direction and magnitude of our RD estimates. In this case, we took advantages of another source of variation, namely the timing of the DST policy. We implement a difference in differences research strategy and compare the amount of criminal activity between those years where the DST was in place to those where it was delayed. Again, we only found a significant increase in crime at sunset hours and no significant variation at other hours of the day.

We extent our results to identify some possible mechanisms associated with the large variation in criminal activity. Our basic estimates can be interpreted as responses to the variations in ambient light associated with the interaction between supply and demand-for-offenses. Supply-side responses are related to potential offenders’ actions and in particular, to the extent that more (less) hours of ambient light deter (stimulate) them to offend. On the other hand, a demand-side response refers to victim’s behavior who can subsequently alter the set of criminal opportunities available precisely because of the variation in ambient light. We can expect that a variation in ambient light induced by DST policy may potentially affect both agents in different directions, and without specific information describing both agents we cannot be certain about the actual mechanism that is driving the result. For instance, an extension of sunlight in the evening hours can encourage people to spend more time outdoors, which may also potentially alter the protection measures potential victims adopt which can be subsequently assimilated by offenders. In that sense, we study some possible adaptive responses associated with the shock in ambient light imposed by DST. In that vein, we investigate the extent to which DST policy causes a substantial variation on the time-commuting pattern of the population. We use Metro ridership data at the same frequency level of our previous estimates for the same period of analysis, and we detect no significant variation at any hour of the day. Although Metro ridership is a broad measure of victim’s behavior, this finding suggests that at least the major portion of the crime variation...
is unlikely to be driven by an endogenous reaction in the commuting pattern which arguably is a key indicator of victims behavior.

Finally, we discuss in more detail possible temporal displacement responses associated with the DST policy. Evidence of substantive time-displacement may limit the scope for action of policies oriented to reduce crime through the use of artificial light in the city. Although we cannot fully reject the presence of some portion of temporal displacement, we find no large nor consistent responses for some particular periods of the day. Overall, our findings suggest that ambient light is a crucial factor of the criminal activity.
3.8 Appendix

Figure 3.13: Distribution of crime reports by hour of the day. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Notes: Figure represents a histogram of crime reports by hours of the day. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which usually occurred after the second Saturday of March, except for the years 2008 and 2010 where the implementation of DST transition was delayed. The sample in this case includes a window of three weeks after (summer) and before (winter) the DST transition in March. Source: Own elaboration.
Figure 3.14: Distribution of crime reports by hour. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Figure represents a histogram of crime reports by hours of the day. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which always occurred after the second Saturday of October. The sample in this case includes a window of three weeks after (summer) and before (winter) the DST October transition. Source: Own elaboration.
Figure 3.15: Distribution of crime reports by hour of the day. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Notes: Figure shows histograms of crime reports by hours of the day for different years. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which usually occurred after the second Saturday of March, except for the years 2008 and 2010 where the implementation of DST transition was delayed. The sample in this case includes a window of three weeks after (summer) and before (winter) the DST transition in March. Source: Own elaboration.
Figure 3.16: Distribution of crime reports by hour of the day. All crimes: Santiago 2005-2010 around Spring DST transition (Oct)

Notes: Figure represents a histogram of crime reports by hours of the day considering different windows of days after and before the DST implementation day. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which always occurred after the second Saturday of October. The sample in this case varies based on the size of the window but always includes the same number of days after (summer) and before (winter) the DST transition in October. Source: AUPOL, own elaboration.
Figure 3.17: Distribution of crime reports by hour of the day. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Notes: Figure represents a histogram of crime reports by hours of the day considering different windows of days after and before the DST implementation day. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which usually occurred after the second Saturday of March, except for the years 2008 and 2010 where the implementation of DST transition was delayed. The sample in this case includes a window of three weeks after (summer) and before (winter) the DST transition in March. Source: Own elaboration.
Figure 3.18: Scatterplot of Log-Crime incidence and days relative to DST transition by daytime period. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Each figure corresponds to a scatterplot of the average log-crime and day relative to the DST transition. Black lines connect the predicted values estimated from a regression for each period of time and at each side of the threshold. We used log of crime incidents for each day-period as dependent variable using several controls (day of the week fixed effects, days relative to the DST transition). Each regression is estimated separately for each side of the threshold to accounts for sharp changes in the dependent variable. The cutoff is defined as the actual DST and the sample is restricted to 21 days at both sides of the threshold.
Figure 3.19: Scatterplot of Log-Crime incidence and days relative to DST transition by
daytime period. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Each figure corresponds to a scatterplot of the average log-crime and day relative to
the DST transition. Black lines connect the predicted values estimated from a regression
for each period of time and at each side of the threshold. We used log of crime incidents for
each day-period as dependent variable using several controls (day of the week fixed effects,
days relative to the DST transition). Each regression is estimated separately for each side of
the threshold to accounts for sharp changes in the dependent variable. The cutoff is defined
as the actual DST and the sample is restricted to 21 days at both sides of the threshold.
Figure 3.20: Linear adjustment of residuals of log crime estimated at each side of the threshold by daytime hours. All crimes: Santiago 2005-2010 around October DST transition (Spring).  

Notes: Each figure corresponds to local linear adjustments at each side of the threshold using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the same is restricted to 21 days at both sides of the threshold. Source: Own elaboration.
Figure 3.21: Quadratic adjustment of residuals of log crime estimated at each side of the threshold by daytime hours. All crimes: Santiago 2005-2010 around October DST transition (Spring).

Notes: Each figure corresponds to local linear adjustments at each side of the threshold using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the same is restricted to 21 days at both sides of the threshold. Source: Own elaboration using AUPOL.
Figure 3.22: Fractional Polynomial adjustment of residuals of log crime estimated at each side of the threshold by daytime hours. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Each figure corresponds to local linear adjustments at each side of the threshold using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the same is restricted to 21 days at both sides of the threshold. Source: Own elaboration.
Figure 3.23: Linear adjustment of residuals of log crime estimated at each side of the threshold at Sunset hours. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Notes: Each figure corresponds to local linear adjustments at each side of the threshold at sunset hours using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the same is restricted to 21 days at both sides of the threshold. Similar figures for others daytime periods and using different adjustment of the running variable and its interaction with the treatment variable are in the Appendix section (Figures 8.6.d-8.6.f). Source: Own elaboration.
Figure 3.24: Scatterplot of Log-Crime incidence and days relative to DST transition by daytime period. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Notes: Each figure corresponds to a scatterplot of the average log-crime and day relative to the DST transition. Black lines connect the predicted values estimated from a regression for each period of time and at each side of the threshold. We used log of crime incidents for each day-period as dependent variable using several controls (day of the week fixed effects, days relative to the DST transition). Each regression is estimated separately for each side of the threshold to accounts for sharp changes in the dependent variable. The cutoff is defined as the actual DST and the sample is restricted to 21 days at both sides of the threshold.
Figure 3.25: Scatterplot of Log-Crime incidence and days relative to DST transition by daytime period. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Notes: Own elaboration using AUPOL. Each figure corresponds to a scatterplot of the average log-crime and day relative to the DST transition. Black lines connect the predicted values estimated from a regression for each period of time and at each side of the threshold. We used log of crime incidents for each day-period as dependent variable using several controls (day of the week fixed effects, days relative to the DST transition). Each regression is estimated separately for each side of the threshold to accounts for sharp changes in the dependent variable. The cutoff is defined as the actual DST and the sample is restricted to 21 days at both sides of the threshold.
Figure 3.26: Linear adjustment of residuals of log crime estimated at each side of the threshold by daytime hours. All crimes: Santiago 2005-2010 around March DST transition (fall).

Notes: Each figure corresponds to adjustments at each side of the threshold using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the same is restricted to 21 days at both sides of the threshold. Source: Own elaboration.
Figure 3.27: Quadratic adjustment of residuals of log crime estimated at each side of the threshold by daytime hours. All crimes: Santiago 2005-2010 around March DST transition (fall)

Notes: Each figure corresponds to adjustments at each side of the threshold using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the same is restricted to 21 days at both sides of the threshold. Source: Own elaboration.
Figure 3.28: Fractional Polynomial adjustment of residuals of log crime estimated at each side of the threshold by daytime hours. All crimes: Santiago 2005-2010 around March DST transition (March)

Notes: Each figure corresponds to adjustments at each side of the threshold using the running variable at the horizontal axis. The cutoff is defined as the actual DST and the same is restricted to 21 days at both sides of the threshold. Source: Own elaboration.
Table 3.5: RD estimates of the DST transition by daytime period. All crimes: Santiago 2005-2010 around Spring DST transition (October)

<table>
<thead>
<tr>
<th></th>
<th>Night</th>
<th>Night</th>
<th>Night</th>
<th>Day</th>
<th>Day</th>
<th>Day</th>
<th>Sunrise</th>
<th>Sunrise</th>
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<td>0.059</td>
<td>0.098</td>
<td>-0.0811</td>
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<td>-0.0441</td>
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</tr>
<tr>
<td></td>
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<td>(0.04)</td>
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<td>(0.05)</td>
<td>(0.09)</td>
<td>(0.07)</td>
<td>(0.07)</td>
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<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Summer*Days2</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>DoWeek FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td>Year FE</td>
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<td>Y</td>
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<td>210</td>
<td>210</td>
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<tr>
<td>R2</td>
<td>0.264</td>
<td>0.307</td>
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<td>0.573</td>
<td>0.584</td>
<td>0.092</td>
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</table>

Notes: Regressions consider log of crime incidents as dependent variable and includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which always occurred after the second Saturday of October. The sample in this case includes a window 17 days after (summer) and before (winter) the DST transition in October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Table 3.6: RD estimates of the DST transition: Sunset hours. All crimes: Santiago 2005-2010 around Fall DST transition (March)

<table>
<thead>
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<th></th>
<th>Night</th>
<th>Night</th>
<th>Night</th>
<th>Day</th>
<th>Day</th>
<th>Day</th>
<th>Sunrise</th>
<th>Sunrise</th>
<th>Sunrise</th>
</tr>
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<tbody>
<tr>
<td>Winter (D)</td>
<td>-0.0225</td>
<td>-0.00819</td>
<td>0.0466</td>
<td>0.0905</td>
<td>0.0783</td>
<td>0.158</td>
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<tr>
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<td>(0.05)</td>
<td>(0.08)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.10)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Days</td>
<td>Y</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td>Days2</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Summer*Days</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
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<td>Y</td>
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<tr>
<td>Summer*Days2</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
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<td>N</td>
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</tr>
<tr>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
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<td>Y</td>
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<td>Y</td>
<td>Y</td>
<td>N</td>
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<tr>
<td>R2</td>
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<td>0.496</td>
<td>0.412</td>
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</table>

Notes: Regressions consider log of crime incidents as dependent variable and includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which always occurred after the second Saturday of October. The sample in this case includes a window 17 days after (summer) and before (winter) the DST transition in October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Figure 3.29: Distribution of crime reports by hour of the day. All crimes: Santiago 2005-2010 around False DST transition (several months)

Figure represents a histogram of crime reports by hours of the day. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to a false DST schedule which is assumed to happen after the second Saturday of each month. Sample in this case includes a window of three weeks after (summer) and before (winter) the false DST transition in each month. Source: AUPOL, own elaboration.
Table 3.7: RD estimates of winter by Offenses and daytime periods during DST transition. Santiago 2005-2010 around Fall DST transition (March)

<table>
<thead>
<tr>
<th>Offense</th>
<th>Night</th>
<th>Day</th>
<th>Sunset</th>
<th>Sunrise</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Crimes</td>
<td>0.0199</td>
<td>0.135*</td>
<td>0.209*</td>
<td>0.0204</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.08)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Robbery</td>
<td>0.103</td>
<td>0.137</td>
<td>0.317**</td>
<td>-0.113</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
<td>(0.11)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Larceny</td>
<td>0.245</td>
<td>0.113</td>
<td>0.236</td>
<td>-0.0479</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.11)</td>
<td>(0.17)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Vehicle Theft</td>
<td>-0.168</td>
<td>0.13</td>
<td>0.11</td>
<td>0.221</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.12)</td>
<td>(0.17)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Theft from vehicles</td>
<td>0.0495</td>
<td>0.0501</td>
<td>0.198</td>
<td>0.0718</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
<td>(0.12)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>Burglary w/People</td>
<td>-0.149</td>
<td>0.0343</td>
<td>0.26</td>
<td>-0.107</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.09)</td>
<td>(0.19)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Burglary w/o People</td>
<td>-0.0449</td>
<td>0.0143</td>
<td>0.131</td>
<td>0.0304</td>
</tr>
<tr>
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<td>(0.12)</td>
<td>(0.12)</td>
<td>(0.19)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>Other robbery</td>
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</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.17)</td>
<td>(0.18)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>Theft</td>
<td>0.129</td>
<td>0.239*</td>
<td>0.217</td>
<td>0.312</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.10)</td>
<td>(0.14)</td>
<td>(0.17)</td>
</tr>
</tbody>
</table>

Notes: This Table contains estimates from 36 regressions. Each regression considers log of crime incidents as dependent variable and includes all crimes reported excluding injuries and domestic violence incidents. Summer refers to the period before DST transition which usually occurred after the second Saturday of March. All estimates are calculated using the same regression which includes the running variable (days), an interaction term between days and summer, day of the week fixed effects and year fixed effects. The sample is restricted to include 17 days before and after the DST transition in fall. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
CHAPTER 3. CRIME-TIME

Figure 3.30: Distribution of crime reports by hour of the day. All crimes: Santiago 2005-2010 around False DST transition (several months)

Notes: Figure represents a histogram of crime reports by hours of the day. It includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to a false DST schedule which is assumed to happen after the second Saturday of each month. Sample in this case includes a window of three weeks after (summer) and before (winter) the false DST transition in each month. Source: AUPOL, own elaboration.
Figure 3.31: Histogram of RD estimates by Day of the Year. Robbery: Santiago 2005-2010 around Sunset hours

Notes: Figure represents a histogram of RD coefficients estimates using equation (1) for every day of the year. We exclude the days after December 15th and before April 15th to avoid both strong seasonality effects associated with summer and DST Fall transition. In all regressions sample includes a window of three weeks after (summer) and before (winter) the false DST transition. Dashed line represents the value of our true DST transition in Spring. Source: AUPOL, own elaboration.
CHAPTER 3. CRIME-TIME

Figure 3.32: RD coefficients sensitivity to days at each side of the threshold by daytime period. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Each point represents the RD estimate of summer using a sample restricted to a bandwidth of days indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable and it includes all crimes reported excluding injuries and domestic violence incidents. Summer refers to the DST schedule which always occurred after the second Saturday of October. All estimates are calculates using the same regression which includes a quadratic function of the running variable (days) interacted with the treatment variable, day of the week fixed effects and year fixed effects.
Figure 3.33: RD coefficients sensitivity to days at each side of the threshold by daytime period. All crimes: Santiago 2005-2010 around Spring DST transition (October)

Notes: Each point represents the RD estimate of summer using a sample restricted to a bandwidth of days indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable and it includes all crimes reported excluding injuries and domestic violence incidents. Summer refers to the DST schedule which always occurred after the second Saturday of October. All estimates are calculates using the same regression which includes a cubic function of the running variable (days) interacted with the treatment variable, day of the week fixed effects and year fixed effects.
Figure 3.34: RD coefficients sensitivity to days at each side of the threshold by daytime period. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Each point represents the RD estimate of winter using a sample restricted to a bandwidth of days indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable and it includes all crimes reported excluding injuries and domestic violence incidents. Winter refers to the period after DST transition which usually occurred after the second Saturday of March. All estimates are calculated using the same regression which includes the running variable (days), an interaction term between days and winter, day of the week fixed effects and year fixed effects.
Figure 3.35: RD estimates of summer by Hour. All crimes: Santiago 2005-2010 around Fall DST transition (March)

Notes: Each point represents the RD estimate of a regression using a sample restricted to the hour indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable and it includes all crimes reported excluding injuries and domestic violence incidents. Winter refers to the period before DST transition which usually occurred after the second Saturday of March. All estimates are calculated using the same regression which includes the running variable (days), an interaction term between days and winter, day of the week fixed effects and year fixed effects. The sample is restricted to include three weeks before and after the DST transition in fall.
Figure 3.36: Diff-in-diff estimates by hour of the day. All crimes: Valparaso 2005-2010 around Fall DST transition (March)

Notes: Figure represents hourly estimates of diff-in-diff regression. Each regression is estimated using a two-hour window period and the coefficient plotted represents the initial hour of the period. The dependent variable is log of crime incidents and includes all crimes reported excluding injuries and domestic violence incidents. Summer and winter refer to the DST schedule which usually occurred after the second Saturday of March, except for the years 2008 (March 29th) and 2010 (April 4th) which are used in this case as controls. The sample in this case is restricted to the period between the earliest DST March transition between the treatment (March 8th) and control groups (March 29th).
Table 3.8: RD estimates by Offenses using two-hour periods during DST transition. Santiago 2005-2010 around Spring DST transition (October)

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Rob</th>
<th>Larc</th>
<th>VehTh</th>
<th>ThfVeh</th>
<th>BwP</th>
<th>Bw/oP</th>
<th>ORob</th>
<th>Thef</th>
</tr>
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<td>[1-2]</td>
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<td>(0.12)</td>
<td>(0.11)</td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.13)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>[3-4]</td>
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<td>-0.0731</td>
<td>0.107</td>
<td>-0.0981</td>
<td>-0.0573</td>
<td>0.114</td>
<td>0.0274</td>
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</tr>
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<td>(0.15)</td>
<td>(0.12)</td>
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<td>(0.11)</td>
<td>(0.12)</td>
<td>(0.16)</td>
<td>(0.13)</td>
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<tr>
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<td>(0.11)</td>
<td>(0.14)</td>
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<td>(0.12)</td>
<td>(0.13)</td>
<td>(0.18)</td>
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<tr>
<td>[9-10]</td>
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<td>-0.235*</td>
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<td>(0.16)</td>
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<td>(0.11)</td>
<td>(0.15)</td>
<td>(0.09)</td>
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<td>(0.12)</td>
<td>(0.11)</td>
<td>(0.10)</td>
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<tr>
<td>[19-20]</td>
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<td>-0.354***</td>
<td>0.0697</td>
<td>-0.164</td>
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<td>-0.231</td>
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<td>(0.12)</td>
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<td>(0.12)</td>
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<td>(0.12)</td>
<td>(0.11)</td>
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<tr>
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<td>-0.0723</td>
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<td>(0.13)</td>
<td>(0.16)</td>
<td>(0.14)</td>
<td>(0.14)</td>
</tr>
</tbody>
</table>

Notes: This Table contains estimates from 108 regressions. Each regression considers log of crime incidents as dependent variable and includes all crimes reported excluding injuries and domestic violence incidents. Summer refers to the DST schedule which always occurred after the second Saturday of October. All estimates are calculates using the same regression which includes the running variable (days), an interaction term between days and summer, day of the week fixed effects and year fixed effects. The sample is restricted to include 17 days before and after the DST transition in October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Table 3.9: RD estimates by Offenses using two-hour periods during DST transition. Santiago 2005-2010 around Fall DST transition (March)

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Rob</th>
<th>Larc</th>
<th>VehTh</th>
<th>ThfVeh</th>
<th>BwP</th>
<th>Bw/oP</th>
<th>ORob</th>
<th>Thef</th>
</tr>
</thead>
<tbody>
<tr>
<td>[1-2]</td>
<td>0.012</td>
<td>0.0626</td>
<td>0.0686</td>
<td>0.0337</td>
<td>-0.0173</td>
<td>-0.0224</td>
<td>0.172</td>
<td>-0.131</td>
<td>-0.0465</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.12)</td>
<td>(0.17)</td>
<td>(0.13)</td>
<td>(0.14)</td>
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<td>(0.11)</td>
<td>(0.19)</td>
<td>(0.12)</td>
</tr>
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<td>[19-20]</td>
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<td>[21-22]</td>
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<td>(0.13)</td>
<td>(0.15)</td>
<td>(0.17)</td>
<td>(0.14)</td>
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</tbody>
</table>

Notes: This Table contains estimates from 108 regressions. Each regression considers log of crime incidents as dependent variable and includes all crimes reported excluding injuries and domestic violence incidents. Winter refers to the DST schedule which usually occurred after the second Saturday of March. All estimates are calculated using the same regression which includes the running variable (days), an interaction term between days and winter, day of the week fixed effects and year fixed effects. The sample is restricted to include 17 days before and after the DST transition in March. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
CHAPTER 3. CRIME-TIME

Figure 3.37: RD coefficients sensitivity to bandwidth size: Overall Daily Effect Property crimes (Left) and Robbery incidents (Right): Santiago 2005-2010 around Spring DST transition

Notes: Figures show RD estimates using different bandwidth sizes using equation (1). Left and right figures show estimates for property crime and robbery respectively. All coefficients are estimates for Spring using days before (winter) and after (summer) DST transition.
Figure 3.38: RD coefficients sensitivity to bandwidth size: Overall Daily Effect Property crimes (Left) and Robbery incidents (Right): Santiago 2005-2010 around Fall DST transition

Notes: Figures show RD estimates using different bandwidth sizes using equation (1). Left and right figures show estimates for property crime and robbery respectively. All coefficients are estimates for Winter using days before (winter) and after (summer) DST transition. Years 2005-2010.
Figure 3.39: RD coefficients sensitivity to bandwidth size: Overall Daily Effect Property crimes (Left) and Robbery incidents (Right): Santiago 2008 and 2010 around Fall DST transition

Notes: Figures show RD estimates using different bandwidth sizes using equation (1). Left and right figures show estimates for property crime and robbery respectively. All coefficients are estimates for April DST transition using days before (winter) and after (summer) DST transition. Years 2008 and 2010.
Table 3.10: RD estimates of Metro Ridership. Santiago 2005-2010 around Spring DST transition (October)

<table>
<thead>
<tr>
<th></th>
<th>[5-6AM]</th>
<th>[7-8AM]</th>
<th>[9-10AM]</th>
<th>[11AM-12PM]</th>
<th>[1-2PM]</th>
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<tr>
<td>Summer</td>
<td>-0.094</td>
<td>-0.273</td>
<td>-0.161</td>
<td>-0.141</td>
<td>-0.107</td>
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<td>(0.101)</td>
<td>(0.087)</td>
<td>(0.088)</td>
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<td>420</td>
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<tr>
<td>R-sq</td>
<td>0.713</td>
<td>0.66</td>
<td>0.494</td>
<td>0.442</td>
<td>0.445</td>
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</table>

Notes: This Table contains estimates from 5 regressions. Each regression considers log of the number of people riding Metro as dependent variable according to (3.4). Summer refers to the DST schedule which always occurred after the second Saturday of October. All estimates are calculated using the same regression which includes the running variable (days), an interaction term between days and summer, day of the week fixed effects and year fixed effects. Since we pooled periods of two hours, we include hour fixed effects in all regressions. The sample is restricted to include 17 days before and after the DST transition in October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Table 3.11: RD estimates of Metro ridership. Santiago 2005-2010 around Spring DST transition (October)

<table>
<thead>
<tr>
<th></th>
<th>[3-4PM]</th>
<th>[5-6PM]</th>
<th>[7-8PM]</th>
<th>[9-10PM]</th>
<th>[11PM]</th>
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</thead>
<tbody>
<tr>
<td>Summer</td>
<td>-0.097</td>
<td>-0.101</td>
<td>-0.087</td>
<td>0.018</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.088)</td>
<td>(0.098)</td>
<td>(0.090)</td>
<td>(0.113)</td>
<td>(0.126)</td>
</tr>
<tr>
<td>N</td>
<td>420</td>
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<td>210</td>
</tr>
<tr>
<td>R-sq</td>
<td>0.435</td>
<td>0.598</td>
<td>0.476</td>
<td>0.337</td>
<td>0.958</td>
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</tbody>
</table>

Notes: This Table contains estimates from 5 regressions. Each regression considers log of the number of people riding Metro as dependent variable according to (3.4). Summer refers to the DST schedule which always occurred after the second Saturday of October. All estimates are calculated using the same regression which includes the running variable (days), an interaction term between days and summer, day of the week fixed effects and year fixed effects. Since we pooled periods of two hours, we include hour fixed effects in all regressions. The sample is restricted to include 17 days before and after the DST transition in October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
CHAPTER 3. CRIME-TIME

This dissertation has analyzed some determinants of the criminal activity in the urban space. I consider aggregate crime rates as a function of a complex interactive system. In chapter one I provide a general and selected overview of the main contributions of the economics of crime literature with a particular focus on the role of prisons in the United States. Among the large body of evidence collected in the recent years, I discuss why an explicit consideration of victim’s behavior in the crime production function represents an important avenue for future research in this field.

Chapter two models crime rates as a function of the interaction between potential offenders and victims. The model has clear theoretical implications that are empirically tested analyzing a particular type of crime (e.g. robberies in the public transport system). Basically, I show how variation in victim’s propensity to resist can explain a substantial portion of criminal activity. In addition, I show that victim’s behavior can alter not only the level but the nature of crime. Then, chapter three considers how this framework can be useful to understand potential mechanisms underlying usual empirical estimates in the economics of crime literature. This chapter presents empirical estimates of the effect of ambient light on criminal activity and has clear implications regarding the role of incentives on crime. Although in this case we cannot fully distinguish offender and victim’s behavior, the fact that we find no endogenous victim’s reaction suggests that most of the action is driven by potential offenders. Overall, this dissertation provides evidence regarding the role of incentives, identifying specific policy changes or situational deviations whose effects in terms of criminal victimization can be equivalent to important public policy interventions. In that sense, it attempts to enlarge the growing body of scientific understanding regarding criminal activity in urban areas.
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