ISSN 1755-5361

University of Essex

Department of Economics

Discussion Paper Series

No. 758 January 2015

Police Disruption and Performance: Evidence from Recurrent Redeployments within a City

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Police Disruption and Performance: Evidence from Recurrent Redeployments within a City*

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January, 2015

Abstract

More policing reduces crime but little is known about the mechanism. Does policing deter crime by reducing its attractiveness, or because it leads to additional arrests of recurrent criminals? This paper provides evidence of a direct link between policing and arrests. During shift changes a peculiar redeployment of police patrols belonging to separate police forces disrupts policing and lowers the likelihood of clearing robberies with an arrest by 30 percent. There is no evidence that criminals exploit these dips in police performance. A back of the envelope calculation suggests that incapacitation explains 2/3 of the elasticity between robberies and policing.

Keywords: police, crime, incapacitation, deterrence, arrests, deployment, quasi-experiment, shift changes
JEL classification codes: K42; H00

*I would like to thank the Police Chief of Milan (*Questore di Milano*) for providing the data, as well as Mario Venturi and his staff for sharing their knowledge on robberies and policing. I would also like to thank Orley Ashenfelter, Matthew Freedman, Jens Ludwig, Lance Lochner, Marco Manacorda, Emily Owens, David Rivers, Ben Vollard, and seminar participants at the University of Surrey, Collegio Carlo Alberto, Cornell University, Université du Québec à Montréal, Queen Mary University, Western University, the 2012 Al Capone workshop, and the 4th Transatlantic Workshop on the Economics of Crime for their comments.

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1 Introduction

Over the last 15 years more and more evidence in the economics of crime literature has shown that more policing reduces crime.[1][2] But the mechanism behind is still unknown and has recently been called a "black box" (Cook et al., 2011, Durlauf and Nagin, 2011). Two channels could potentially be at work: deterrence and incapacitation. On the one hand, criminals might be deterred from committing a crime by the mere presence of more policemen, or, more generally, by the perception that the certainty of punishment increases when there is more policing (see the seminal contributions of Becker, 1968, Ehrlich, 1973).

On the other hand, the additional police forces might be "productive" and *clear* more crimes, which would lead to more arrests and convictions, hence incapacitating the arrested criminals from committing additional crimes for as long as they are in custody.[3] A necessary condition for the presence of incapacitation is that additional policing increases the likelihood that after committing an offense criminals are put in custody. This paper's main aim is to provide evidence on such mediating mechanism (see Ludwig et al., 2011, for a discussion on mediating mechanisms).

Recent papers exploit changes in highly visible and predominantly static police deployment following terrorist attacks (Di Tella and Schargrodsky, 2004, Draca et al., 2011, Klick and Tabarrok, 2005, Machin and Marie, 2011). These are ideal conditions to measure deterrence, and all four papers observe localized and abrupt changes in crime rates.[4]

This study focuses on a different but common type of policing, automobile patrolling. According to recent policing statistics nearly 7 in 10 local police officers had regular patrolling duties, and almost all U.S. local police departments use regularly scheduled automobile patrols (Reaves, 2011). As such, this research complements previous research. Changes in mobile patrolling could be harder to detect and might be less prone to generating deterrence.

I use detailed data on the universe of commercial robberies that happened in Milan between January 2009 and June 2011, and the contemporaneous exclusive deployment

[1] See, among others, Buonanno and Mastrobuoni (2011), Corman and Mocan (2000), Evans and Owens (2007), Levitt (1997), Chalfin and McCrary (2013).

[2] In contrast a large criminological literature has generally failed to find significant impacts of police on crime, even in quasi-experimental studies (see Sherman, 2002, Skogan and Frydl, 2004, for an overview of such evidence). Sherman and Weisburd (1995) represents a notable exception.

[3] The productivity of police departments is often judged based on clearance rates (Garicano and Heaton, 2010, Mas, 2006).

[4] Skogan and Frydl (2004) review the criminology literature on the effectiveness of policing. The studies that evaluate the effect of policing on crime generally find that crime spikes during strikes. But strikes are perfectly predictable and known, and when they happen most of the change in crime seems to be driven by the sudden and complete lack of deterrence.

of two very similar police forces together with a unique rotating mechanism of police deployment to estimate the effect of a disruption in policing on a binary variable measuring whether such crimes have been cleared.[5] Until the mid-nineties, in all major Italian cities two police patrol forces (the *Polizia*, the police, and the *Arma dei Carabinieri*, the gendarmerie) were patrolling the streets.[6] Then, in an attempt to rationalize resources, cities were divided into three parts, assigning exclusive control to the *Polizia* and to the *Carabinieri* of 2/3 and 1/3 of the city.

The assignment of these areas rotates during shift changes four times a day, inducing patrols to poorly coordinated and time-consuming trips across the city. When there is a shift change police patrols that are finishing their shift head for the headquarters, while police patrols that are starting their shift drive from the headquarters towards the area they have been assigned. The large black circle on the map of Milan shown in Figure 1 shows the location of the two headquarters. Both are located in the very city center, a few hundred yards from each other.[7] The map shows also the exact location of each commercial robbery that happened in Milan by the intervening force. [8] Overall, the *Polizia* and the *Carabinieri* cover the entire city, and, based on Google maps, the victimized businesses are on average a 15 minute drive from the two headquarters.

The underlying rotation mechanism is shown in Figure 2. Each panel represents a smaller version of Figure 1, depicting police coverage by shift (night, morning, midday, evening) and rotation day. For example, the two Panels rotation "day 1, night" and rotation "day 1, morning" imply that during rotation days of type 1 at 7am *Carabinieri* patrols move from the North-Western area to the North-Eastern one. At the following shift change they move to the Southern area, etc.

Whether such shift changes disrupt policing depends on institutional rules, the behavior of police officers, and chance. According to the law shift changes should occur directly

[5]About thirty years ago a few papers have looked at this mediating mechanism (Carr-Hill and Stern, 1973, Craig, 1987, Mathur, 1978, Thaler, 1977, Wolpin, 1978). Using simultaneous equations models with non-testable identification restrictions, most of these papers find support the existence of both deterrence and incapacitation. In particular, in Thaler (1977) individual crime-level clearance rates, similar to the ones used in this study, are shown to respond strongly to changes in the number of police officers. The issue is that such deployment is likely to be endogenous. In the criminology literature little evidence is found of an effect of policing on clearance rates (Cordner, 1989, Skogan and Frydl, 2004), but again deployment of police forces is likely to be endogenous.

[6]Italy is not the only European country with two major police forces. In addition to the police forces France deploys the Gendarmerie, the Netherlands the Royal Marechaussee, Portugal the National Republican Guard, Romania the Gendarmerie, Poland the Military Gendarmerie, and Spain the Guardia Civil.

[7]The exact addresses are Via Fatebene Fratelli and Via della Moscova.

[8]Section 2 focuses on the temporal and spatial distribution of robberies by the intervening police force, confirming that such reassignments do take place.

on the street at the hour sharp, thus doubling the presence of police cars around that time. Since shift changes happen at 7am, 1pm, 7pm, and 12am, incoming patrols operate up to the hour, and outgoing ones operate past the hour. Whenever police patrols follow the law, during shift changes the number of visible police cars doubles.[9] Yet, at any given point in time only one car is formally on duty, and so the number of *active* cars stays constant.

But there is evidence, discussed in Section 2.2, that at times the number of functioning police cars is insufficient to perform all shift changes on the street. When this happens incoming and outgoing patrols share the same police car, and patrols drive from the area they were securing to the police headquarters, which are located in the city center (the exact location is shown in Figure 1), before performing what the *Polizia* calls a "car on car" shift change *(macchina su macchina)*. While the switching of the crews inside the headquarters takes a few minutes, driving from the assigned neighborhood to the headquarters and back to the newly assigned neighborhood takes on average 30 minutes. Moreover, the severity of the consequent disruption in police patrolling is increasing in the distance between the assigned neighborhood and the headquarters. I use the exact time of the robbery and the exact distance from the headquarters measured in driving time to predict whether the incoming or the outgoing police patrol could have reached the victimized commercial business on time. Since there is no information on the incidence of car shortages across shift changes and city areas, this study estimates the "intention to treat" effect of shift changes.

In particular, information about the switching of the areas of deployment, as well as on the exact time of robberies and the exact distance between robbed businesses and the police headquarters, allows me to estimate the effect of disrupting police patrolling on a binary variable measuring whether the robbery has been solved (meaning that at least one arrest has been made), an often used measure of police productivity.[10] According to the law shift changes happen at the hour sharp, and any unobserved delay biases the results towards zero. Despite such bias, I find a 30 percent reduction in the likelihood of solving a crime through an arrest during shift changes. The disruption is entirely driven by robberies that happen far from the police headquarters.

[9] To assess the importance of the lack of coordination across the two police forces and the resultant lack of continuity of control over a territory, later I exploit the fact that the *Polizia* retains control in one of the three rotating areas.

[10] According to the Milan *Polizia* clearing a robbery means that at least one robber has been identified, leading to a future arrest. But most times the identified offender chooses to collaborate with the police–identifying his fellow offenders–to receive sentence reductions. For this reason I use clearances and arrests as synonymous.

Given how important it is for policy purposes to disentangle deterrence from incapacitation,[11] in Sections 2.2 and 5 the study addresses in great detail whether an endogenous response of criminals can explain the observed reduction in clearances during shift changes.

The richness of the micro-level data allows me to perform a battery of tests for such endogeneity. The tests are based not only on the choice of time and location of robbers, on the composition of robbers during shift change periods, but also on the dynamic (learning) behavior of robbers. Yet the single most powerful test is that there is no evidence that during shift changes robbers are more likely to target businesses which are located away from the headquarters, which, given the results on clearances, even considering counteracting strategies by the police forces, is shown to be a dominant strategy.

There are several factors that make it hard for criminals to select shift changes as the best time to rob businesses: i) when shift changes are done according to the law, deterrence should doubles rather than being reduced (even if the number of *active* police cars is fixed); ii) if robbers knew the timing of shift changes, they would still need to predict where the shortage of police cars is going to take place, and the police forces have an incentive to keep the location unpredictable;[12]; iii) when there are "car on car" shift changes, for most of the time patrols that are driving from or toward the headquarters are still visible and generate deterrence;[13]; iv) several special police forces, whose cars are indistinguishable from the other ones, follow different shifts;[14] [15] and, finally, v) despite the doubling of

[11]Deterrence does not imply additional costs, while incapacitation does (criminals are put on trial, spend time in jail, might receive job training and counseling once released, etc.).

[12]In Section 2.2 I discuss equilibria in a game between police forces and robbers to determine the location of robberies and "car on car" shift changes.

[13]Like many historical European cities, Milan has a highly chaotic network of streets (a map is shown in the Online Appendix Figure 1), and it would be hard for anyone to predict from the direction whether the Police cars are driving to the headquarters.

[14]The *reparti mobili* (mobile force), the *squadre mobili* (mobile teams), the cars of the neighborhood *Polizia* and *Carabinieri* offices (*commissariati di polizia* and *stazioni dei Carabinieri*), the *poliziotti di quartiere* (neighborhood police officers), and the *motociclisti* (motorbikers) operate over the entire city without rotating, and follow two shifts (8am-2pm and 2pm-8pm) that differ from the ones followed by the rotating corps. For example, according to Bassi (2011) 3 out of 20 local *Polizia* offices in Milan have an operating *Polizia* car, and such car as well as most cars of the other special forces would not be distinguishable from the about 15 cars that operate for the *Polizia di Stato* headquarters, which are the ones which rotate and try to contrast the most common crimes, including robberies. In short, during shift change periods several *Polizia* and *Carabinieri* cars are potentially driving around the city but the patrol cars that, following an incident, get called by the *Polizia* or *Carabinieri* operation center are either on their way toward the headquarters, or on their way from the headquarters to the incident location, or, whenever there is a shortage of cars, potentially inside the headquarters.

[15]Even if the change in policing was somehow visible, the lack of (negative) deterrence might still be related to what criminologists call residual deterrence (Sherman, 1990). Some evidence suggests that the deterrence effect of highly visible police crackdowns persists well beyond their cessation, possible due to criminal perceptions that adjust slowly over time. These adjustments might arguably be even less likely to occur when the changes in policing are short-lived (a few minutes) and erratic (dependent on

forces prescribed by the law during shift changes, this is the first study providing evidence of a reduced productivity of policing. Criminals would have to base their decisions on their own experience and on the experiences of their criminal acquaintances. While one cannot rule out such a "common" wisdom about shift changes, such communality would be easier to detect in the data, and there is no evidence of it.

In Section 6 I discuss under which conditions the effect of police disruptions on arrests (the mediating mechanism) can be used to learn something about the size of the incapacitation effect. When more policing increases the likelihood of clearing and arresting repeat offenders, under some conditions (large reoffending rates, immediate incarceration, and sufficiently long sentences), crime rates are inversely proportional to clearance rates, implying that the elasticity of crime with respect to policing equals the negative elasticity of clearance rates with respect to policing. Province level scatter plots of crime rates against clearance rates (see Section 6.2) provide some suggestive evidence about such inverse proportionality.[16]

The panel dimension of the data allows me to measure actual reoffending rates (not just rearrest rates). More than one third of robbers will reoffend until they are arrested. Arrested robbers await in jail for trial, and are convicted with probability that is almost one. Combining the estimated effects on police productivity (clearances) with the total elasticity of crime with respect to policing one can separate incapacitation from deterrence. The implied split between deterrence and incapacitation for police patrols that are fighting robberies against businesses is 1/3 and 2/3.

2 The Ideal and the Quasi-experiment

Most researchers have focussed on the deterrence effect of policing, and, until recently, the main strategy was to use aggregate crime regressions (Durlauf et al., 2010).[17]

the availability of police patrols).

[16]The Appendix Figure 11 shows that for thefts, burglaries, and pick-pocketing there is evidence on incapacitation is weaker, and is totally absent for assaults.

[17]Levitt (1998) uses such regressions to identify deterrence and incapacitation from the differential response of specific crime rates (e.g. robbery rates, theft rates, etc.) to the clearance rates of other types of crimes.The identification assumption is that deterrence for a specific crime does not depend on the clearance rate for other crimes. Rapes and robberies appear to be the only crimes for which incapacitation appears to be larger than deterrence (their relative size is 2 for rapes and 1.2 for robberies). An additional paper, McCormick and Tollison (1984), uses very detailed information on sports rather than crime, and finds that when the number of college basketball referees increased from two to three the number of fouls dropped by more than 30 percent, though the effect might also be driven by strategic interactions between referees. Due to coding errors the initially very precise estimates lost some significance (Hutchinson and Yates, 2007, McCormick and Tollison, 2007).

Section 6 shows that not only does one need strong assumptions to move from an individual behavioral model of crime to aggregate crime regressions, but that such aggregation is even more problematic when criminals are not (forcefully) assumed to be onetime criminals. When aggregating over recurrent criminals clearance rates not only generate linear deterrence effects but also highly convex incapacitation effects.[18]

Due to the limitation of such aggregate crime regressions, researchers have recently used more disaggregated data over time and space, and quasi-experimental designs to uncover the mechanism behind the reduction in crime when policing increases. Two recent papers, Di Tella and Schargrodsky (2004), and Draca et al. (2011) use terrorism-related events to estimate the crime-police relationship.[19] [20] Since the terror attacks induce a highly visible increase in police presence in particular locations, the observed drop in crime is likely due to deterrence.[21]

2.1 The Ideal Experiment

In the ideal experiment aimed at measuring incapacitation the "treatment," meaning the increase in policing, should not only be randomly assigned but also unnoticeable. Any noticeable change in police presence could potentially generate deterrence. And, as a response to deterrence, criminals might avoid compliance by either moving out of a treated region or by waiting until treatment is over. In principle the ideal way to measure the incapacitation effect of having more police patrolling would be to keep the same number of police cars in treated and control areas–generating the same deterrence effects–but vary

[18] Avi-Itzhak and Shinnar (1973)'s and Shinnar and Shinnar (1975)'s model of recurrent criminals would lead to the same conclusions. In line with the evidence about incapacitation based on micro-level data, in Section 6.2 shows that for some crimes, including robberies, aggregate crime rates are convex with respect to clearance rates.

[19] A third paper, Klick and Tabarrok (2005), uses data that are disaggregated over time. The paper exploits terror alerts and a time-series of daily crimes in the city of Washington D.C..

[20] A set of studies in criminology uses random changes in patrols to test the effectiveness of police forces, but again the focus is on crime rates, and no evidence, again, is provided about the mechanism (Sherman, 2002).

[21] In particular, Di Tella and Schargrodsky (2004) use very disaggregated street-level data on car thefts, before and after the 1994 terrorist attack on the main Jewish center in Buenos Aires. The redeployment was highly visible as the police forces would be stationing in front of Jewish centers around the city. The authors find that the number of car thefts dropped in those areas that received police protection. Incapacitation is unlikely to generate an effect that is circumscribed to a few streets, and so the drop in crime is most likely attributable to increased deterrence. Draca et al. (2011) use London borough-level crime data before and after the July 2004 terrorist attacks. Their changes in police deployment comprises mobile police patrols, but officers were also posted to guard major public spaces and transport nodes, particularly tube stations, making the redeployment highly visible. Since the changes in crime coincide not only with the increased police presence but also with its reduction after 6 weeks of high terror alerts, the evidence is consistent with deterrence.

the number of cars that are fully operational. The remaining cars would act as "placebo" cars.

Since incapacitation has not just immediate but also cumulative effects, a pre-post policy intervention in one city would generate a gradual and potentially hard to identify reduction in crime rates. Moreover, as criminals learn about the increased incapacitation, deterrence would also emerge (assuming the effective police cars lead to additional arrests). Alternatively, one could use spatial variation in "treatment." In order to avoid interactions across treated and non-treated areas driven by the mobility of criminals (ensuring what the policy evaluation literature calls the stable-unit-treatment-value),[22] one could randomly assign treatment to large areas, or better entire cities. But again, perceptions about the increased productivity of the police force might generate increased deterrence.

Instead of measuring differences in crime rates between treatment and control, one can move one step back and measure differences in clearances and arrests (the mediating mechanism).[23] Exploring such mediating mechanism allows one to change the time and the area of treatment, reducing concerns of interactions across treated and non-treated areas, as well as concerns about increased deterrence in the treated areas.

This comes at the price of having to compute the incapacitation effects based on the arrests. To compute the incapacitation effect of policing from an arrest one needs to know i) whether the arrest lead to certain prison time, and ii) the counterfactual number of crimes the arrested robbers would have attempted. Section 6 deals with the conditions that need to be satisfied to measure incapacitation effects based on arrests, while the next two Sections describe the quasi-experiment and the differences between the ideal and the quasi-experiment.

2.2 The Quasi-experiment

The quasi-experiment that was briefly described in the Introduction is based on quasi-random redeployment of two police forces, the *Polizia* and the *Carabinieri*, within the same Italian city, Milan, during shift changes. Italy has two separate police forces that share the same functions and objectives. The *Carabinieri* were the royal police force, the

[22]The Online Figure 14 shows that groups of robbers tend to operate in selected parts of the city. But these clusters tend to be quite large, and movements between businesses located at opposite extremes on the map are not uncommon.

[23]Incapacitation of active criminals might in principle induce also new entry of criminals Freeman (1999). In other words, the supply of criminals might be elastic. While little is known about such interactions, the supply of robbers operating in major cities is arguably less elastic. In Milan, for example, there are on average less than two robberies per day, while there are thousands of potential commercial businesses to be victimized. The rest of the paper assumes an inelastic supply of robbers.

gendarmerie, and despite the 1945 referendum that ended the monarchy in favor of the republic, they were not dismantled.

Each force is responsible for keeping law and order each in a different part of the city.[24] For police deployment purposes the city is divided into 3 areas, North-West, North-East, and South (see Figure 2); the Southern area is the largest, covering between 40 and 50 percent of the city and 43 percent of the robberies (another 34 percent of the robberies happen in the North-Eastern part of the city and the rest in the North-Western part). At any given point in time one area is under the control of the *Carabinieri*, and two under the control of the *Polizia*.

Such assignments rotate clockwise about every 6 hours, in concert with shift changes. Given that there are two forces, three areas, and four 6-hour shifts within a given day, the *Carabinieri* cover the same area during the same 6-hour shift only every three days. This induces quasi-random variation in the days of the month, days of the week, and 6-hour shift in the geographic coverage of police forces. Inside each area there are about 7 to 10 cars that cover around 120 square kilometers (40 square miles).

Each square and each dot in Figure 2 represents a different victimized commercial business that based on the rotation mechanism has been assigned to the *Carabineri* or to the *Polizia*. Outliers in the recurrent pattern are driven by officers who, as mentioned before, are part of the smaller non-rotating *Polizia* or *Carabinieri* forces. The neighborhood police forces, the mobile forces, and the motor-bikers follow the 8am-2pm and 2pm-8pm shift.

As previously discussed, shift changes are likely to disrupt policing when there is a shortage of police cars, which is unpredictable. I learned about the frequent shortage of police cars from private conversations with Milan Police officers. While the Milan police force has been unwilling to provide factual evidence of this, I found local newspaper interviews of Milan Police Union members complaining about the scarcity of working police cars. According to such interviews about 50 percent of cars cannot perform the shift outside of the headquarters. When an extra outgoing police car is missing the shift has to be performed inside the headquarters.[25]

Whenever there is no such shortage, the number of visible police cars doubles, doubling the potential deterrence effect. The assignments are binding, which means that even

[24] The rotating system is in place in all major Italian cities.

[25] According to the Police Union SIULP in Milan there are between 15 to 20 *Polizia* cars patrolling the streets, but on average only 25 cars are fully working (Biondini, 2011, Editorial Office, 2011, Garofalo, 2013). I was not able to find the corresponding numbers for the *Carabinieri*. Given that the two forces are equally funded the numbers are likely to be similar.

when there are two overlapping police cars in a neighborhood only one is responsible for maintaining law and order. The other car would either be heading towards the assigned area (before the hour) or towards the headquarters (past the hour).

Moreover, to reduce the complexity of the assignments procedure, there are no attempts to accommodate delays. The *Polizia* and the *Carabinieri* are by all means two separate entities: for example, they have separate emergency telephone numbers (112 and 113), and the operators forward the call to the assigned police force depending on the exact time of the call and the exact location of the crime.

Delays of either the outgoing (the patrols might be in the middle of a task) or the incoming cars (the car might be broken, or the officers might be late), could either increase deterrence or additionally disrupt policing depending on the availability of overlapping cars. The longer it takes to drive in and out, which depends on traffic and distance, the more likely it is that for some time streets are less patrolled. There are no data on average speed or on response times for police cars, or data recording the exact location of police cars over time. This means that there is no direct measure of the average reduction in police presence during a specific shift change,[26] but Figure 2 does imply that police patrols are moving in and out of the headquarters around shift changes.[27]

As a proxy for congestion and relative speed one can look at the number of cars that enter the city center and at the average speed of city buses (which is only available starting at 5am). The Online Appendix Figure 13 shows that there is no congestion at night (average speed of buses is between 14 and 16 km/h), while the peak inflow of cars is between 8 am and 9 am, which corresponds to the lowest average speed for public buses (8 km/h). At 7 am, 1 pm, and 7 pm the inflow of cars into the city center is close to 5000 cars every half hour, and the average speed of public buses is close to 10 km/h. The inflow of cars might be a poor proxy of congestion in the afternoon when most cars drive out of the city. In the evening the average speed of public buses starts increasing at 6pm, but overall shift change intervals during daytime are not subject to exceptional congestion.

[26]Thaler (1977) finds little evidence that response time matters, though response time is likely to be endogenous.

[27]The estimates measure intention to treat effects, or upper bounds of the true reduction in the likelihood of making an arrest.

2.3 Addressing the Differences Between the Ideal and the Quasi-Experiment

The main difference between the ideal experiment and the actual one is that the time of the shift changes is recurrent and thus predictable. But what is not predictable is whether there is a shortage of police cars, and when and where such shortage disrupts policing. Shortages are driven by unpredictable car breakdowns due to accidents or car failures.

If criminals knew that, in spite of the law, in some occasions there are not enough cars to run the shift changes on the streets, they might still prefer the lottery of facing twice as many police cars or half the number of police cars over the normal number of police cars. Especially if they knew that when there is an overlapping presence of police patrols only one would be fully operational. But the choice of a particular time could also be driven by unobserved or partially-observed factors (i.e. opening hours, cash holdings, weather conditions, crowding, visibility, etc.).

A more stringent test for whether robbers are knowledgable is based on their choice of the location of victims during shift changes. Disruption is likely to be increasing with the distance from the headquarters, but this also depends on the strategies put in place by the police forces.[28] In order to reduce unpaid overtime the *Polizia* and the *Carabinieri* might be tempted to select overlapping patrols to be close to the headquarters.[29] Since the disruption of "car on car" shifts increases with the distance from the headquarters, robbers would have a strong incentive to target victims that are located far from the headquarters.

But rather than minimizing overtime the police forces might schedule overlapping patrols to minimize disruption. This would immediately imply that they would have to randomize. One can think of their problem as a zero-sum game where the police force maximizes and robbers minimize arrest probabilities. For simplicity one can think that during a "car on car" shift change both agents need to choose whether to target victims (the robber) or protect victims (the police force) that are located either close or far from the headquarters. A disagreement in choices benefits robbers while an agreement benefits police forces. Such a game has only mixed strategy equilibria, and so one would expect the police to randomize the assignment of "car on car" shift changes.[30]

[28]According to private conversations I had with police officers, the "car on car" shift changes are not chosen strategically.

[29]According to a contractual agreement the extra minutes spent on the street during overlapping police patrolling are unpaid.

[30]The Online appendix Table 12 shows the normal form game where the payoffs have been chosen to resemble the estimated differences in clearance rates.

Moreover, in an attempt to minimize the expected disruption due to a shortage, the police would have to assign more frequently ordinary shift changes to those neighborhoods that are more vulnerable, more victimized, and where disruption is greater. Since the duration and the intensity of the disruption is increasing in the distance from the police headquarters (see Section 4.2), the police forces would have an incentive to more frequently maintain ordinary shift changes in neighborhoods that are located farther away from the headquarters. Yet, because of the increased disruption, knowledgable criminals would be more likely to target businesses that are distant from the police headquarters.

Summing up, based on the evidence of disruption during shift changes and no matter what the objective function of the police force is, an excess mass of robberies against commercial business that are located far from the headquarters during a shift change would be evidence that robbers exploit shift changes, and that shift changes generate negative deterrence. The formal test is a difference in differences in the fraction of robberies depending on location (below/above median distance from the headquarters) and time (shift change status) of the robbery. This is the simplest and yet most powerful test for whether criminals are aware of the vulnerability of law enforcement during shift changes.

The additional advantage of the difference in difference test is that it controls for any unobserved factors that influence the optimal timing of robberies as long as they do not depend on the distance from the headquarters (see Section 5).

The data also allow for a whole battery of additional tests that for brevity can be found in the Online Appendix B. Selection that is driven by knowledgable and smart robbers would typically produce positive answers to some of the following questions: Is the *modus operandi* of robberies that happen during shift changes different from all the others?[31] Are able robbers, defined as those who are more unpredictable and, therefore, more successful, more likely to target businesses during shift changes? Does controlling for the experience of robbers, measured by the number of successful robberies, alter the results? Are robbers who happened to commit a robbery during a shift change (and thus might have learned about the deficiencies in policing) more likely to do so again in their subsequent robbery? Do the findings differ when focussing on robbers who for the first time happen to perform a robbery during a shift change, and therefore are less likely to have deliberately chosen such periods? These tests are increasingly able to detect whether at least some robbers are aware of the disruptive power of shift changes.

[31] The most intuitive way to test whether there is such a selection is to perform a balance test depending on the time of the robbery. In Mastrobuoni (2011) I show that more able bank robbers tend to get larger hauls with specific modus operandi (e.g. they are more likely to use firearms). Thus, one would expect robberies that happen during shift changes to be associated with larger hauls.

3 Milan Crime Data

The area under study, which comprises the municipality of Milan (*Comune*) as well as part of the smaller neighboring municipalities around it (*Provincia*) compares well to cities like Philadelphia (Pennsylvania). The population of the *Comune* is equal to 1.34 million (vs. 1.5 million in Philadelphia), the land area under study is close to 350 square kilometers (134 square miles) which is exactly equal to the land area of Philadelphia.[32][33] Though while Philadelphia has a rectangular grid plan, Milan, like many historical European cities (e.g. Rome, Paris, London, etc.) has irregular city blocks and a highly chaotic network of streets.

For investigative purposes the anti-robbery *Polizia* department of Milan collects individual-level information on robberies and robbers (not yet for the other crimes). After each robbery, even those assigned to the *Carabinieri*, the *Polizia* collects all kinds of information about the perpetrators, the victim, the loot, etc.[34]

The Polizia complements the information contained in patrol reports surveying the victims, and collecting any available information that is recorded by nearby surveillance cameras. Their main purposes are i) to identify recurrent perpetrators in order to predict their future offenses, and ii) to provide prosecutors with forensic evidence. This method is known as *predictive policing*.

While in the absence of victimization surveys of commercial businesses exact victims' reporting rates cannot be computed, according to police investigations these are close to 100 percent. Evidence of this is based on criminals' confessions. Since most robbers are caught *in flagrante delicto* they have an incentive to plead guilty in order to receive a 1/3 sentencing reduction (*patteggiamento*). Indeed, in 2008 and 2009 all but one arrest lead to convictions for an average of 4 years in jail. Prosecutors ask the arrestees to list all their previous offenses. Again, there is a sentencing incentive to do so whenever a criminal believes that the the prosecutor possesses evidence on past crimes. In exchange for confessing multiple crimes the prosecutor agrees to consider these crimes as one "continued" crime (*reato continuato*) for which the sentence is considerably gentler than the sum of sentences that correspond to the single crimes.

According to the *Polizia* only in one instance did an arrestee confess a robbery that had not been reported (later the business owner acknowledged this). Businesses might be

[32]One can easily approximate the land area using a circle with a radius between 10 and 11 km (7 miles).

[33]Aggregate crime rates and clearance rates show that within Italy the city does not represent an outlier (see Section 6.2).

[34]The *Polizia* force does not record the exact locations of police cars in every moment in time (such data would not just be difficult to store but also quite hard to analyze).

aware that the only way to increase police patrolling in their neighborhood is by reporting the crime.[35]

3.1 Summary Statistics and Balance Test

I have been given access to a subset of the variables used by the *Polizia* to predict the crimes between January 2008 and June 2011. The many variables that describe in great detail the physical appearance of robbers were not added to the dataset, while those that describe the *modus operandi* of the robbers were added.

In the data each observation is a separate robbery, and 353 happen within 15 minutes of a shift change. The remaining 1,814 do not. The 16 percent of robberies that fall within those 30 minute periods are higher than what a uniform distribution would predict, which is going to be discussed in great detail when testing for deterrence (Section 5).

The summary statistics by shift change status are shown in Table 1. Shift change status is a 0/1 variable that measures the change in shift 15 minutes before up to 15 minutes after the beginning of a shift; for example, 6.45am-7.15am around the start of the 7am-1pm shift. The likelihood of clearing a robbery (by means of an arrest) during a shift change is 9.1 percent, while it is 14.8 percent during the rest of the day. The third group of columns shows that this raw difference is significant at the 1 percent level. The only other variables that differ significantly are the fraction of robberies that happen during the 30 minutes that precede the shops' closing time. Since the exact opening hours of each business are not known, I use two proxies for the closing times. I divide businesses into 23 homogenous categories and take the maximum and the 90th percentile of the observed time of the robberies.[36] While some businesses close around the 7pm shift change (bakeries and jewelers), most close around 8pm.

The *Polizia* uses information taken from surveillance cameras together with very detailed descriptions by the victims about the robbers to link offenders across robberies. The *Serial robbers* variable identifies robbers who have been linked (70 percent of robberies are linked to such serial robbers). Figure 3 shows a screen-shot of the software used to reconstruct such series. The variable "*Number of the series*" indexes the robberies that are linked with each other in a chronological manner. Such number is later used as a proxy for experience.

The Police variable indicates whether the *Polizia* handled that particular robbery. While the city is divided into 3 parts and the *Polizia* is responsible for 2 parts, the

[35] On top of this, businesses often need a police report for insurance purposes.
[36] The Online Appendix Table 11 shows the individual closing times.

fraction of robberies that is handled by the *Polizia* is slightly larger than expected (73 against 67 percent). Before 2010 the *Polizia* was using a predictive policing software called *Keycrime* to catch serial robbers, a software which was later shared with the *Carbinieri*. A few additional variables describe the *modus operandi* of the robberies, as well as the value of the stolen loot. Notice that the variables that are assumed to signal ability, like loot, or the use of firearms (see Mastrobuoni, 2011) do not seem to vary depending on the shift change status, indicating that more able robbers are not targeting those periods (additional tests for deterrence, based on the entire distribution of the loot are shown in Section 5).

4 The Effect of Disrupted Policing on Clearance Rates

4.1 Simple Differences and the Event Study Design

The simplest way to estimate the effect of a shift change on clearing a robbery is to compute the difference between the probability of clearing a robbery during a shift change and the probability of clearing a robbery during the rest of the day.

I take 30 minute periods around the time of the four shift changes T_j ($j = 1, ..., 4$). Later I will define the intervals based on Google's estimated distance between the location of the robbery and the headquarters. For now, setting t to be the time the robbery ends,[37] the j-th intention to treat (ITT) shift change effect is simply:

$$\delta_j = E(Y|\,|t - T_j| \leq 15') - E(Y|\,|t - T_j| > 15'),$$

and can be estimated on robbery n perpetrated by the group of offenders i using the following regression function:[38]

$$Y_{i,n} = \alpha + \sum_{j=1}^{4} \delta_j I(|t_{i,n} - T_j| \leq 15') + f(t_{i,n}) + x'_{i,n}\beta + \epsilon_{i,n}, \tag{1}$$

where $f(t_{i,n})$ represents the underlying daily evolution of clearance rates, and when $|t_{i,n} - T_j| \leq 15'$ the counterfactual clearance rates during a shift change. The other regressors $x_{i,n}$ are observed characteristics of the robbers and of the robberies.

For now, let us consider the case where $f(t_{i,n})$ is constant and β is equal to zero.

[37] The median duration of bank robberies, which are the most complicated ones, is just 3 minutes.

[38] All the regression are estimated using least squares regressions and clustering the standard errors by group of offenders i.

Table 2 shows that the probability of clearing a robbery (the clearance rate) is equal to 9.1 percent during shift change periods and equal to 14.8 percent otherwise (as in the Summary statistics table). Such simple difference, estimated using a linear probability model, is significant at the 1 percent level.

Panel B of the same table shows that the difference is driven by the shift changes that happen during the day (92 percent of robberies that happen during a shift change period happen either at 1 pm, 22 percent, or at 7 pm, 70 percent). With the exception of the 18 robberies that happen during the midnight shift change, clearance rates are lower during shift changes than during the rest of the day. The 7 am shift change, with just 11 robberies shows that one issue is sample size. None of the 7 am robberies are cleared and, despite the small sample size, this gives rise to a large and significant difference. Small success or failure probabilities with small samples complicates testing of binomial distributions, as small observed changes in the number of observed successes can lead to large differences in the test statistics.

A rule of thumb to approximate the discrete binomial distribution with the normal one is that the sample size times the success and the failure probability are both larger than 5. Some researchers use the cutoff value 10. Since the overall clearance rate is 0.15, this implies that the approximation is good when the period's sample size is larger than 33 or 66.[39]

Since there are on average 45 observations in each half-hour interval, in order to gain statistical power I collapse the four shift changes into one period. This quadruples the average number of observations in each half-hour interval, improving statistical power.

There are two alternative models that can be used to estimate the shift change effect. The first is to collapse the shift change dummy variables in Eq. 1 by constraining δ_j to be a constant across j. Moving the intervals by d multiples of 30 minutes from the true shift change periods the regression can be amended to compute placebo shift change effects δ^d:

$$Y_{i,n} = \alpha + \delta^d \sum_{j=1}^{4} I(|t_{i,n} - T_j + d \cdot 30'| \leq 15') + f(t_{i,n}) + x'_{i,n}\beta + \epsilon_{i,n}. \tag{2}$$

[39]For example, treating the $n = 11$ robberies that happen around 7 am as a independent Bernoulli trials, the likelihood of observing 0 arrests with a *known* overall arrest rate of 15 percent is 16.7 percent, which is low, but above the 10 percent level. I simulated size discrepancies between the actual and the nominal size when using a linear probability model of clearing a robbery with clustered standard errors. In line with the heuristic rule, the actual size of the test converges to the nominal one when there are about 50 to 60 observations in each group. With 50 to 60 observations statistical power (at a 10 percent level with an effect equal to -0.04) is about 30 percent, but is twice as large with 250 observations.

When $d = 0$ the model estimates the ITT effect δ^0.

The other model estimates the shift change effects using an event study design. I center time around the shift changes: $t_{i,n} - T_j$.[40] defining d different event time intervals centered around $t_{i,n} - T_j \pm d \cdot 30'$, where the excluded time intervals are the ones with $d = \pm 1$ and $d = \pm 2$, thus adjacent to the shift changes. With the event study regression

$$Y_{i,n} = \alpha + \sum_{d \in \{\pm 5, \pm 4, \pm 3, 0\}} \delta^d \sum_{j=1}^{4} I(-15' < t_{i,n} - T_j + d \cdot 30' \leq 15') + x'_{i,n}\beta + \epsilon_{i,n}, \qquad (3)$$

δ^0 measures the difference in the probability of clearing a case between 30 minute shift change periods, for example 6.45am-7.15am, and the two adjacent periods 5.45am-6.45am and 7.15am-8.15am.[41]

The advantage of the event time model is that all the placebo coefficients ($d \neq 0$) are estimated at once. If chance was driving the results, the coefficient δ^0 (the true shift change period) would be similar to many other δ^ds.

4.1.1 Results from The Event Study Design

Table 3 shows the estimated coefficients of a linear probability model of a robbery being cleared modelled as in Equation 3.[42] The coefficient on the *Shift change interval (SCI)* represents the difference between the likelihood of clearing a robbery that happened within 15 minutes of a shift change, and one that happened during the two adjacent one-hour time intervals.

Column 1 does not include additional covariates x, while Column 2 includes the two variables that failed the balance test.[43] Given that the balance test was done only for the shift change periods, in Column 3 I also include the value of the stolen loot, a *Polizia* dummy, a south and a north-west dummy, year by month dummies, day of the week dummies, a firearm dummy, a knife dummy, a daylight dummy, whether the robbery is against a bank, and the average number of thefts that are committed within the same 30 minutes.[44]

[40] Online Figure 16 shows the relationship between the time of the day and the event time.

[41] The results are robust to the exclusion of longer adjacent time intervals, while choosing a shorter baseline interval reduces the precision of the estimates, but not their level.

[42] Given that in column 1 the covariates are discrete and the model is saturated the conditional expectation functions can be properly parameterized as a the linear model. Using a probit model in all three specifications (Columns 1 to 3) the marginal effects are almost identical to the linear probability case.

[43] In line with the small differences shown in the balance test, having no other regressors or adding additional ones does not alter any of these results.

[44] Controlling, in addition, for the potentially endogenous predicted (by the victim) age of the robbers

Just before and after the shift changes clearance rates are equal to 13.6 percent, and drop by -4.5 percentage points during shift changes. The only other significant coefficient (at the 10 percent level) is the one related to the interval that follows by 2 and a half hours the shift changes. Adding the two variables that failed the randomization test leaves the shift change coefficient almost unchanged, and non of the other 30 minute period is statistically speaking different from zero. In line with the results from the randomization table when I control for all the additional variables the coefficient on the shift change period remains unchanged. Moreover, controlling for the additional regressors all the other coefficients are precisely estimated to be close to zero.

4.1.2 Results from the Semi-Parametric Difference Design

Instead of using just the adjacent periods as a baseline, one can retain statistical power by comparing the shift change period with the underlying evolution of clearances within a day (see Equation 2). Rather than comparing the shift changes to nearby periods, one compares them to their counterfactual evolution based on the entire sample of robberies. The underlying evolution can be modelled using different semi-parametric methods, and the hypothesis can be further tested by generating placebo shift changes $\delta^d, d \neq 0$.

Given that the time of the day repeats itself every 24 hours this is the ideal setup to model time using periodic functions. There is a large literature in mathematics and in statistics on using series of sines and cosines, infinite and truncated Fourier series, to approximate any smooth function.[45] Since time repeats itself in cycles such approximations are even more valuable.[46]

The underlying evolution of the probability of clearing a case becomes a function of sines and cosines $f(t) = \sum_{j=1}^{k}(\gamma_{0j}\cos(j \times 2\pi H_{i,n}) + \gamma_{1j}\sin(j \times 2\pi H_{i,n}))$, where $H_{i,n}$ indicates the time of day standardized to lie between 0 (midnight) and 1 (one minute before midnight). Based on cross validation the optimal choice for k is equal to 2.[47]

Controlling for the underlying evolution of clearances, Table 4 shows that using periodic functions for $f(t)$ the shift change effect is between -4.9 and -5.0 percentage points

and perceived nationality of the robbers, as well as for their experience does not alter the results.

[45]A weighted trigonometric series of sines and cosines is called a trigonometric polynomial of order k. Trigonometric polynomials have been used to approximate functions since Fourier's 1822 "The analytical theory of heat."

[46]Andrews (1991) shows that under some smoothness conditions a truncated Fourier series estimated using least squares converges to the true periodic function. While such smoothness conditions do not apply to clearance dummies the approximations turn out to be good.

[47]This choice serves a similar role here to the bandwidth parameter for non-parametric kernel estimations. See the Online Appendix Section A.1.

(similar to what was found in the event study design). Using a quartic in time or cubic splines the results are similar.[48] Given the better fit and the previous discussion the rest of this study is going to estimate $f(t)$ using either the Fourier series, or the event study dummies (*de facto* the nearby time intervals).

The estimated true and placebo shift change coefficients δ^d with the corresponding 95 percent confidence intervals are shown in Figure 4. There is a clear reduction in the coefficients around the true shift change, and, in line with the results based on the event study, the only significant differences are around the shift changes. Notice that the negative coefficients at ± 30 minutes might be driven by a misclassification of treatment, as at times it might take more than than 15 minutes to reach a given location. In the next Section I will exploit the exact time it takes to reach a victimized businesses. Moreover, since in placebo regressions the truly treated time interval contributes to the underlying evolution ($f(t)$), the placebo coefficients tend to be larger than zero.

4.2 Shift Change Effects Depending on the Distance from the HQ

Up until now the shift change "treatment" status has been based on the time of the robbery, irrespective of the distance from the headquarters. But around shift changes *Polizia* and *Carabinieri* patrols need to drive in and out of the headquarters, which are located in the city center (see Figure 1). This implies that unless the police forces use specific strategies to cover the city outskirts (see Section 2.2, during shift changes businesses located farther away from the headquarters are likely to be less protected.

The simplest way for taking distance into account is to divide businesses depending on whether their distance is above or below the median distance of all businesses from the police headquarters. Such a dichotomous distinction allows me to setup a difference in difference strategy. In particular, I estimate Equations 2 and 3 interacting the 30 minute time interval dummies with the above median and below median distance dummies.

Such a difference-in-difference strategy controls for any unobserved factors that might drive the choice of the time of the robbery without also influencing the choice of the location (i.e. the exact business hours, the visibility conditions, and other unobserved criminal strategies and constraints). Columns 1 and 2 of Table 5 show the estimated effects when using the Fourier series and the event time strategy.

The two set of estimates are very similar. During shift changes the reduction in the

[48]The Online Figure 12 shows that except during the night time, where the sample size is quite small, the more flexible semi-parametric functions are similar to each other. The quartic of time, instead, tends to oversmooth the series.

likelihood of clearing a case is indeed entirely driven by businesses that are located more than 15 minutes away from the headquarters (the median time to reach a victimized business according to Google Maps). For brevity I do not include all the interacted event time dummies, but all those that are not shown are precisely estimated to be close to zero. The difference between the shift change effects when the distance is above of below the median has a p-value of 5 percent when using the more efficient semi-parametric Fourier series while it is close to 10 percent when using the less efficient non–parametric event time model. Later, when testing for deterrence I am going to exploit this additional difference.

Given that the *Polizia* might potentially better coordinate the shift changes whenever they keep control over the same area across contiguous shifts (I define such shifts as "smooth"),[49] in Columns 3 and 4 I separate the "smooth" and "non-smooth" shift changes. There do not seem to be large differences based on whether the police forces retains control over an area, showing that lack of coordination happens also within the *Polizia*, but lack of statistical power disallows any further inferences.

It follows from these results that using 15 minutes before and after to define the intention to treat status might not always be correct. In order to take the exact distance from the headquarters into account, I define whether the police patrol was potentially too far from the crime scene to reach it on time. I use the actual time $\tau_{i,n}$ it takes to travel from the headquarters to the crime scene, and given that Google's estimated durations for Italy do not take traffic into account, I inflate the time $\tau_{i,n}$ by a constant $\kappa \geq 1$ to define the "intention to treat status:"

$$I(|t_{i,n} - T| \leq \kappa\tau_{i,n}). \tag{4}$$

Table 6 presents the estimated δs using κ from 1 to 1.5 in increments of 1/10, based on Fourier regressions (Columns 1 and 2) and on $\pm 1h15m$ around shift change samples (Columns 3 and 4). In line with a more precise treatment status, the results are larger than before. The largest shift change effects are obtained when using $\kappa = 1.2$, meaning that for police patrols Google's estimated travel time is 20 percent lower than the actual one, or that patrols tend to anticipate the end or delay the start of their shift.

[49]Given that there are 2 areas out of three that are covered by the *Polizia* the fraction of such areas is approximately equal to 30 percent.

5 Testing for Deterrence

There are several statistics that could signal the presence of deterrence related to shift changes. Deterrence would lead to differences in the distribution, composition, as well as evolution of robberies.

5.1 Distribution of Robberies and Congestion

Let us start with the distribution. The distribution of robberies by time of the day shows that the excess mass is driven by robberies that happen when businesses are about to close, around both lunch time and dinner time (see Figure 5, time goes from 0 to 24). Most business are only open during the day, typically between 8 am and 8 pm, which is when most robberies take place.[50]

5.1.1 Congestion

Shift changes are close to such spikes, and thus one might worry that the productivity of the police patrols suffer because of congestion. Yet, since there is on average less than one robbery in each shift (exactly 0.375), this channel is unlikely to be an important one.[51] A simple way to test for congestion is to restrict the analysis to the set of first robberies of the day.

If in a given day the police officers are busy investigating the first robbery, for the subsequent ones the productivity may be harmed. This would be particularly troublesome in case of congestion. Table 7 computes the shift change effects focussing on the very first robbery of the day that a given police force has to deal with. If anything, congestion appears to bias the effects towards zero.

[50]Figure 6 shows the distribution for major crime categories.

[51]In order to see whether other crimes produce congestion effects during shift changes, I use the average daily number of thefts in 15 minute intervals that happened between 2009 and 2010 in Milan. These tables are based on the official police reports collected by the Central Police Department in Rome (*Servizio Analisi Criminale*). The daily number of thefts are shown in Figure 6. I reduce the heaping at [0-14] minute and [30-44] minute intervals shown in the Online Appendix Figure 15 distributing a mass proportional to the relative degree of heaping to the [15-29] and [45-59] minute intervals. The assumption is that over the entire day thefts are uniformly distributed over the four 15-minute intervals. While there are on average only 1.5 robberies each day, every 15 minutes there are about 3 thefts. None of the average number of thefts shows a clear spike during shift changes. The numbers are typically higher either before or after the shift changes. Bag-snatching and pick-pocketing crimes tend to be high during the entire day, while burglaries spike in the morning when victims are likely to realize the theft. Other kinds of thefts spike around 8pm. I would like to thank Ernesto Savona from *Transcrime*, the Joint Research Centre on Transnational Crime, for sharing these data.

5.1.2 Distribution

In the absence of congestion, a mass around shift changes might still signal that criminals know about potential police disruptions around shift changes.[52] And if the more knowledgable robbers were also the more able ones, heterogeneity in knowledge would generate heterogeneity in ability, which might bias the shift change effects downward.

First I test for a mass point around shift change periods, while later I will test for differences in ability between robbers depending on whether they select such periods.

In order to generate a single test statistic I mimic the analysis performed for the likelihood of clearing a case, estimating Equation 2 and 3 using the number of robberies as the dependent variable. But before running the regressions it is useful to look at the histogram of the the time centered around shift changes. Figure 7 shows the histogram in 15 minute bins of the *event time* (left panel) and of the *absolute value of event time* (right panel). Taking the absolute value collapses the potential jump 15 minutes before shift changes (the first vertical line, -0.25) and the potential jump 15 minutes after shift changes (the second vertical line, +0.25) into one potential jump (+0.25). In line with the time of the day histogram (Figure 5) there is evidence of a discontinuity at -0.25 and at +0.25, but no matter which histogram one looks at, the direction of the jump is opposite of the one that (lack of) deterrence would generate.Yet, Figure 7 does show evidence of a drop 45 minutes before and after shift changes (0.75 of one hour).

But these drops do not seem to be related to an endogenous response of robbers when exploiting the heterogeneity based on distance from the headquarters. Unobserved conditions faced by robbers (i.e. the exact opening time of businesses, the visibility on the street and inside the business premises due to weather conditions, sunlight, etc.) as well as their individual constraints (i.e. their working hours in legitimate jobs, etc.) could be contributing to such drop. Since these conditions and constraints are not changing with the distance from the headquarters and the police disruptions were concentrated far from the headquarters, one can compare clearances of robberies that happen far from the headquarters with those that happen near the headquarters.

Figure 8 shows the two histograms conditional on whether the businesses are below or above the median distance from the headquarters. There are no differences at 45 minutes and also very little evidence of differential drops at 15 minutes: while for distances above the median the mass of robberies that happen during a shift change is slightly larger (though as will be shown not in a significant way), the jump is still positive instead of negative at +0.25 (15 minutes).

[52] Evidence that thefts and burglaries do not cluster around shift changes is shown in Figure 6.

There is also no evidence that the "smoothness" of the shift change matters for the distribution of event time. Whether these differences are significant is shown in Table 8. The table presents Poisson model estimates of shift change effects, where the dependent variable is the number of robberies aggregated by 15 minute periods (96), by area (north-east, north-west, south), by median distance from the headquarters (HQ), and by shift change day type (from 1 to 3). So there are a total of 1,656 observations. All estimates can be interpreted as semi-elasticities. While there is some evidence that robberies spike around shift changes when compared to control periods (in the event study approach the control period is 1 hour and 15 minutes from the shift change interval), there is no evidence that during shift changes robbers are more likely to target businesses that are located farther away from the headquarters, which is when and where the entire disruption takes place. Columns 3 and 4 show that the number of robberies does not differ depending on whether the *Polizia* maintains control over the area (*smooth changeover*).

5.2 Discontinuities among Regressors

While it has been completely ruled out that congestion is driving the reduction in police performance during shift changes, and there is no evidence that during shift changes many robbers are actively selecting businesses that are located far from the police headquarters, balance tests can tell us whether those who do select the right time and place appear to be more able criminals. Beyond making a safe escape, the other most important measure of success is the value of the loot.

While the summary statistics table showed that the loot, as well as the other characteristics of robbers and robberies during shift changes differ little with respect to the rest of the day, there might still be discontinuities *around* shift changes. The upper panel of Table 9 performs the test for discontinuities for covariates around the shift change, using the Fourier as well as the $\pm 1h15min$ before and after shift change sample. The lower panel shows the difference-in-difference estimate, where the additional difference is based on whether the distance between the victim and the headquarters is above the median.

The simple differences coincide with the differences shown in the summary statistics (Table 1). Even the difference-in-differences show little evidence of ability difference, and they typically go in the opposite direction: robbers are less likely to be armed, and the groups of robbers tend to be smaller.

Arguably the single most important variable to measure ability is the value of the stolen good, and average differences might hide some heterogeneity (Bitler et al., 2006, see). Figure 9 displays the whole cumulative distribution functions depending on the shift change status focussing on robberies that happen close to shift changes ($\pm 1h15m$). Using a Kolmogorov-Smirnov test one cannot reject that the two distribution functions are the same.

5.3 Summary of Additional Tests

For brevity several additional deterrence tests are in the Appendix Section B. In short, there is no evidence that robbers who have the ability to be more unpredictable, because they target businesses that are less clustered in space, are more likely to target shift changes. There is also no evidence of learning about the opportunity given by shift changes: robbers who targeted a shift change are not more likely to target it in later robberies. There is also no evidence that the shift change effects are closer to zero for robbers who for the first time target a shift change, and therefore are less likely to be part of a selected group of more knowledgable and possibly able robbers.

6 Consequences for Incapacitation

When a robbery is cleared and *repeat* offenders are arrested *and convicted* for a *sufficient period of time*, changes in clearance rates induce changes in incapacitation.

Clearing a robbery is almost always synonymous with at least one arrest.[53] But will the robbers spend time in prison?

Most robbers are caught *in flagrante delicto* and are deemed at high risk of recidivating, and by law will spend their time in prison before the trial.[54] There is no bail system in Italy. Moreover, based on data collected by the *Polizia* the 31 series that were cleared in 2008 led, across arrestees, to a total of 203 years in jail, the 39 cleared in 2009 to 217 years in jail.[55] Given that the average number of robbers per robbery is 1.5, about 100 arrested robbers shared average convictions of about 4 years of jail time (the legal minimum mandatory sentence for robberies is 3 to 4.5 years, depending on the modus operandi).[56] Of these robbers, only one was found not guilty and 4 were given alternative sanctions to prison (e.g. home arrest).[57] Arrests can thus potentially lead to incapacitation effects for the entire time period for which robberies are observed (2008-mid 2011).

[53]According to the *Polizia* two times they waited to make the arrest of identified perpetrators only to gather additional evidence.

[54]About 20 percent of Italian inmates are usually awaiting the initial trial.

[55]For later years many trials are still ongoing.

[56]Most convicted robbers would spend at least 3/4 of the prison sentence before release.

[57]For later years some of the trials are pending.

In order to measure the incapacitation effect one needs to reconstruct the counterfactual number of crimes the arrested robbers would have committed had they been free.Such number depends on the distribution of repeat offenders and their offences, as they are the ones whose arrest would generate a *future* reduction in crime. Typical crime data do not contain any information about repeat offenders and arrest data contain at most information on recidivism, a measure that is projected toward the *past*.

The panel dimension of the Milan records allow me to reconstruct the "survival table" of robbers. Table 10 shows the distribution of robberies based on the "Number of the series." The sample starts with 907 disjoint group of robbers performing a robbery. Of these robberies 136 are cleared immediately (15 percent). Based on the remaining 771 groups, given that 244 perform a second robbery, the recurrence rate (the rate of repeat offenders) is close to 1/3. Depending on what one assumes about the recurrence of the 136 groups who were arrested after the first robbery one can compute quite narrow upper and lower bounds of the recurrence rate. Conditional on having performed a second robbery the recurrence rate jumps to more than 80 percent, reaching almost 90 percent after 4 events. Given that all these estimates are based on the assumption that the *Polizia* perfectly observes each robber, they are likely to be lower-bounds. It is thus safe to say that one in three arrests of robbers who are at their first robbery generate subsequent incapacitation effects. When arrested and convicted recurrent robbers generate much larger incapacitation effects, as they tend to persist in robbing businesses.

6.1 A Model of Repeat Offenders

At this point, in order to quantify incapacitation separately from deterrence it is necessary to formalize the robbers' decision problem.

An individual model of crime where criminals can potentially repeatedly commit crimes complicates the aggregation of crime regressions.[58] At time t an individual decides to commit a crime when his/her expected utility from doing so is positive

$$(1-\pi\left(c\left(p\right),p\right))\,U\left[\hat{Y}\right]-\pi\left(c\left(p\right),p\right)D\left[S\right]-u_t>0,$$

where π is the perceived "clearance rate" (which depends on the true clearance rate c *and* on the level of policing p). $U(\widehat{Y})$ is the utility from the expected loot, and $D(S)]$ the disutility from spending S years in prison; u_t is the opportunity cost from committing a crime at time t (e.g. legal earnings), which is likely to be fairly persistent across

[58]With the exception of repeat offenses the setup is similar to the one used by Durlauf et al. (2010)).

individuals. Such persistence introduces repeat criminal behavior.

The likelihood of committing a crime is

$$F_t = F\left(U\left[\hat{Y}\right] - \pi\left(D\left[S\right] + U\left[\hat{Y}\right]\right)\right),$$

where F is the cumulative distribution function of u_t over the entire population. Without repeat offending (in other words with errors u_t that are independent over time) F represents the crime rate. When aggregate crime regressions are linear in clearance rates c, researchers are assuming that the errors (the outside opportunities) are uniformly distributed.

If, instead, outside opportunities change little over time,[59] and T criminal opportunities arise in a year, the crime rate is not just $F(\bullet)$, but rather

$$C(c) = \sum_{t=0}^{T} F(\cdot)(1-c)^t \approx F(\cdot)\frac{1-(1-c)^{T+1}}{c} \approx \frac{F(\cdot)}{c}.^{60} \tag{5}$$

How does this function depend on c?[61] While $1/c$ is clearly convex, for the cumulative distribution $F(\bullet)$ convexity or concavity depend on the functional form of $\pi(c(p), p)$ and on the shape of the corresponding density around the marginal criminal.[62]

Before using Equation 5 to separate incapacitation from deterrence, it is clear that a convex relationship between crime rates and clearance rates would be separate and additional evidence of incapacitation.

6.2 Aggregate Effects Based on Province-level Crime Data

When using aggregate crime regressions researchers have often assumed that perceived clearance rates equal the true ones, that the distribution of outside opportunities is uniform, and that criminals are onetime offenders. Under these assumptions, based on Equation 6.1, the relationship between C and c is linear: $C(c) \propto U\left[\hat{Y}\right] - c\left(D\left[S\right] + U\left[\hat{Y}\right]\right)$.[63]

[59]According to the Italian Statistical office (www.Istat.it) in 2011 more than half of all unemployed workers were unemployed for more than a year.

[61]Several functional forms have been used in the literature. Among the papers that have estimated the effect of clearance rates on crime rates Levitt (1998) and Glaeser and Sacerdote (1999) use a log-log specification, Machin and Meghir (2004) use a probability odds-log specification, and Mustard (2003) uses a log-level specification.

[62]Avi-Itzhak and Shinnar (1973) and Shinnar and Shinnar (1975) use a more convoluted but also more mechanical model to reach similar conclusions about the relationship between crime and clearance rates.

[63]Since earnings distribution are unimodal, the distribution of outside opportunities is likely to be the same. Assuming that perceived clearance rates equal the true ones ($\pi = c$) the relationship between F

Based on the approximation of Equation 5, adding repeat offenders to the picture crime rates become inversely proportional to c: $C(c) \propto \frac{U[\hat{Y}]}{c} - D[S] - U\left[\hat{Y}\right]$.

Figure 10 plots 20 years of yearly province level aggregate crime rates for robberies and for motor vehicle thefts against the corresponding clearance rates (defined as the number of cleared crimes over the total number of crimes in a year). The relationship is strongly convex, and the simple re-scaled prediction based on $1/c$ fits the data quite well.[64]

While the observed convexity represents external evidence of incapacitation effects, it would be difficult to estimate their magnitude based on aggregate data.[65]

6.3 Implied Incapacitation Effects

Instead of using the aggregate relationship between crime rates and clearance rates, I use the micro-level evidence on clearances $c(p)$ and Equation 5 to estimate the incapacitation effect.

The data do not allow one to precisely measure the reduction in policing during shift changes, but according to the Police Union the average number of working cars is 25, while cars on patrol range between 15 and 20.[66] This means that between 1/3 to 2/3 of patrolling cars need to perform the shift change inside the headquarters. This also means that for the remaining 2/3 to 1/3 of cars the shift change is potentially less disrupting.[67] In order to compute average treatment effect (ATE) one has to divide the shift change effect (the intention to treat effect, ITT) by such fractions. With an estimated ITT which is close to -0.05, the resulting range for the average treatment effect is between -7.5 and -15 percent. A treatment effect of -15 percent would mean that the likelihood of immediately clearing a robbery is close to zero, which is consistent with the fact that most arrested

and c would be decreasing and convex if the marginal criminal's outside option lies below the mode and decreasing and concave otherwise.

[64] On a related note, trying to measure incapacitation using the relationship between arrests and policing would be a mistake. As Levitt and Miles (2004) and Owens (2011) point out, the theoretical predictions about arrest rates are ambiguous. More policing can potentially reduce the arrests in case of deterrence as well as increase them in case of incapacitation. Since Evans and Owens (2007) show that the COPS program reduced overall crime, while Owens (2011) finds no effect of such a program on arrests, there is arguably indirect evidence that deterrence and incapacitation are both present.

[65] Overall clearance rates are known to be subject to measurement errors. For example, the clearance might happen a year after the crime happened. Clearance rates are also subject to selection, as averted crimes are not measured in c (Cook, 1979). Overall clearance rates depend on police enforcement and are thus likely to be endogenous. Moreover, even if F was uniform, the function that links perceived clearance rates to actual ones $\pi(c(p), p)$ could also potentially be non-linear (e.g. robbers might misperceive small probabilities).

[66] The *Polizia* keeps records about the outgoing and incoming police cars for two weeks before destroying such information, but would not disclose such information.

[67] No equivalent statistics are available for the *Carabinieri*.

robbers are caught in *flagrante*.

One can use the ATE together with an estimate of the elasticity of robberies with respect to policing to evaluate the relative strength of incapacitation and deterrence. Using the elasticity estimate from Buonanno and Mastrobuoni (2011) $\frac{\partial C}{\partial p}\frac{p}{C} = -1.1$,[68] and, assuming there is only an incapacitation effect,[69] from Eq. 5 it follows that:

$$\frac{\partial C}{\partial p}\frac{p}{C} = \frac{\partial C}{\partial c}\frac{c}{C} \times \frac{\partial c}{\partial p}\frac{p}{c} = -1 \times \frac{ATE}{c}. \tag{6}$$

Since $\frac{ATE}{c}$ is equal to $\frac{0.05/0.5}{0.15}$ (using the midpoint between a reduction of 1/3 and 2/3), the implied incapacitation elasticity would be equal to -0.67. This would mean that about 2/3 of the total elasticity (-1.1) is due to incapacitation and the remaining 1/3 is due to deterrence. Having in mind that the estimate is likely to translate into an upper bound for incapacitation, the split is not very far from the approximately 50/50 split derived by Levitt (1998).

7 Conclusions

Using precise micro-level information about robberies against businesses coupled with some peculiar rules about shift changes, this paper shows that disrupting police patrolling reduces the likelihood of clearing a robbery (i.e. arresting at least one of the perpetrators).

A battery of highly diverse selection tests suggests that most robbers do not exploit such shift changes, which is likely to depend on their ignorance about such differences in clearance rates. This might in part depend on the fact that except for the time when there is a shortage of police cars and such cars are physically inside the police headquarters, police cars remain visible and might even be present in excess. Moreover, as previously discussed, additional police squads, whose cars are indistinguishable from those which rotate, do not rotate, and follow different shifts.

What can be learned from such a specific "low-visibility" quasi-experimental change in policing? If criminals are usually aware of typical (business as usual) policing levels, the ultimate effect on crime of typical policing would most likely be a combination of deterrence and incapacitation. Much in the same way the redeployment of stationing police

[68] The elasticity estimate is broadly in line with the US evidence. It is slightly lower than Evans and Owens (2007)'s estimate (-1.34), and Lin (2009)'s estimate (-1.86), larger than Chalfin and McCrary (2013)-s preferred estimate (-0.56), and in line with Levitt (1997) (-1.20).

[69] I am also implicitly assuming that there large reoffending rates, incarcerations are immediate, and sentences last at least one year. All of these assumptions are met in the case of Milan robberies but might not be met for other crimes, or other cities.

officers following a terrorist attack are likely to produce an upper bound of deterrence and a lower bound of incapacitation compared to a "typical" police officer–who is neither constantly stationing in front of buildings,[70] nor constantly driving around the city–the Milan shift-changes are likely to produce opposite bounds. The "typical' police officer is likely to be less predictable than a stationing officer, and more predictable than one that is rotating during shift changes.

In terms of policy implications, this paper highlights an issue related to shift changes. During these changes businesses located far away from the headquarters need more patrolling. In order to eliminate the shift change effects the Italian law prescribes to organize the changes out on the street, which requires twice the active number of police cars. A less costly strategy that reduces the shift change effect is to have overlapping shift changes. For example, half of the Pittsburgh Police units change at a specific time, the other half one hour later. If robberies were the only crime, one could also time the shift changes when fewer crimes are committed (the Online Appendix Section A.2 computes an optimal shift change regime without overlapping).

As for optimal number of police cars, the sizable incapacitation effects, at least with respect to robberies, suggest that judiciary spending has to be taken into account when deciding about police staffing.

[70]As in Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005) and Draca et al. (2011).

References

Donald W.K. Andrews. Asymptotic normality of series estimators for nonparametric and semiparametric regression models. *Econometrica*, (2):307–345, 1991.

Benjamin Avi-Itzhak and Reuel Shinnar. Quantitative models in crime control. *Journal of Criminal Justice*, 1(3):185–217, 1973.

Cristina Bassi. Poliziotti a milano, tra gomme a terra e servizi part-time. *Sky.it*, June 13 2011.

Gary S. Becker. Crime and punishment: An economic approach. *The Journal of Political Economy*, 76(2):169–217, 1968.

Sara Biondini. Schiaffo di Pisapia "Militari Inutili, ronde negative". *Libero*, November 8 2011.

Marianne P. Bitler, Jonah B. Gelbach, and Hilary W. Hoynes. What Mean Impacts Miss: Distributional Effects of Welfare Reform Experiments. *American Economic Review*, 96 (4):988–1012, September 2006.

Paolo Buonanno and Giovanni Mastrobuoni. Police and crime: Evidence from dictated delays in centralized police hiring. Technical report, 2011. mimeo.

R.A. Carr-Hill and N.H. Stern. An econometric model of the supply and control of recorded offences in england and wales. *Journal of Public Economics*, 2(4):289 – 318, 1973.

Aaron Chalfin and Justin McCrary. Are U.S. Cities Underpoliced?: Theory and Evidence. Technical report, 2013. mimeo.

Philip Cook, Jens Ludwig, and Justin McCrary. Economical crime control. In *Controlling Crime: Strategies and Tradeoffs*, NBER Books, pages 331–363. National Bureau of Economic Research, Inc, 2011.

Philip J Cook. The clearance rate as a measure of criminal justice system effectiveness. *Journal of Public Economics*, 11(1):135–142, 1979.

Gary W. Cordner. Police agency size and investigative effectiveness. *Journal of Criminal Justice*, 17(3):145 – 155, 1989.

Hope Corman and H. Naci Mocan. A time-series analysis of crime, deterrence, and drug abuse in new york city. *American Economic Review*, 90(3):584–604, June 2000.

Steven G. Craig. The deterrent impact of police: An examination of a locally provided public service. *Journal of Urban Economics*, 21(3):298 – 311, 1987.

R. Di Tella and E. Schargrodsky. Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack. *The American Economic Review*, 94(1):115–133, 2004.

Mirko Draca, Stephen Machin, and Robert Witt. Panic on the Streets of London: Police, Crime and the July 2005 Terror Attacks. *American Economic Review*, 101(5):2157–81, 2011.

Steven N Durlauf and Daniel S Nagin. Imprisonment and crime. *Criminology & Public Policy*, 10(1):13–54, 2011.

Steven N. Durlauf, Salvador Navarro, and David A. Rivers. Understanding aggregate crime regressions. *Journal of Econometrics*, 158(2):306 – 317, 2010.

Editorial Office. Cento volanti ferme in questura. E non ci sono soldi per aggiustarle. *Il Giornale*, November 8 2011.

Isaac Ehrlich. Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy*, 81(3):521–65, 1973.

William N. Evans and Emily G. Owens. COPS and Crime. *Journal of Public Economics*, 91(1-2):181–201, 2007.

Richard B. Freeman. The Economics of Crime. *Handbook of Labor Economics*, 3:3529–3571, 1999.

Luis Garicano and Paul Heaton. Information technology, organization, and productivity in the public sector: evidence from police departments. *Journal of Labor Economics*, 28(1):167–201, 2010.

Pier Paolo Garofalo. Macchine vetuste e mal equipaggiate, ma la polizia funziona. *Il Piccolo*, November 2013.

Edward L. Glaeser and Bruce Sacerdote. Why is there more crime in cities? *Journal of Political Economy*, 107(S6):pp. S225–S258, 1999.

Kevin P. Hutchinson and Andrew J. Yates. Crime on the court: A correction. *Journal of Political Economy*, 115:515–519, 2007.

Jonathan Klick and Alexander Tabarrok. Using terror alert levels to estimate the effect of police on crime. *Journal of Law & Economics*, 48(1):267–79, April 2005.

Steven D Levitt. Using electoral cycles in police hiring to estimate the effect of police on crime. *American Economic Review*, 87(3):270–90, June 1997.

Steven D Levitt. Why do increased arrest rates appear to reduce crime: deterrence, incapacitation, or measurement error? *Economic inquiry*, 36(3):353–372, 1998.

Steven D. Levitt and T. Miles. Empirical Study of Criminal Punishment. *The Handbook of Law and Economics*, 2004.

Ming-Jen Lin. More police, less crime: Evidence from us state data. *International Review of Law and Economics*, 29(2):73–80, 2009.

Jens Ludwig, Jeffrey R. Kling, and Sendhil Mullainathan. Mechanism experiments and policy evaluations. *The Journal of Economic Perspectives*, 25(3):pp. 17–38, 2011.

Stephen Machin and Olivier Marie. Crime and police resources: The street crime initiative. *Journal of the European Economic Association*, 9(4):678–701, 2011. ISSN 1542-4774.

Stephen Machin and Costas Meghir. Crime and economic incentives. *Journal of Human Resources*, 39(4), 2004.

Alexandre Mas. Pay, reference points, and police performance. *The Quarterly Journal of Economics*, 71(3):783–821, 2006.

Giovanni Mastrobuoni. Optimal criminal behavior and the disutility of jail: Theory and evidence on bank robberies. Carlo Alberto Notebooks 220, Collegio Carlo Alberto, 2011.

Vijay K. Mathur. Economics of crime: An investigation of the deterrent hypothesis for urban areas. *The Review of Economics and Statistics*, 60(3):pp. 459–466, 1978.

Robert E McCormick and Robert D Tollison. Crime on the court. *Journal of Political Economy*, 92(2):223–35, April 1984.

Robert E. McCormick and Robert D. Tollison. Crime on the court, another look: Reply to hutchinson and yates. *Journal of Political Economy*, 115:520–521, 2007.

David B. Mustard. Reexamining criminal behavior: The importance of omitted variable bias. *The Review of Economics and Statistics*, 85(1):205–211, February 2003.

Whitney K. Newey, James L. Powell, and James R. Walker. Semiparametric estimation of selection models: Some empirical results. *The American Economic Review*, 80(2): 324–328, 1990.

Emily Owens. Cops and cuffs. mimeo, 2011.

Brian A Reaves. *Local police departments (2007).* U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics, 2011.

Lawrence W. Sherman. Police crackdowns: Initial and residual deterrence. *Crime and Justice*, 12:pp. 1–48, 1990.

Lawrence W. Sherman. Policing for crime prevention. In *Evidence-based crime prevention*, page 295. A Report to the United States Congress, prepared for the National Institute of Justice, 2002.

Lawrence W Sherman and David Weisburd. General deterrent effects of police patrol in crime "hot spots": A randomized, controlled trial. *Justice Quarterly*, 12(4):625–648, 1995.

Shlomo Shinnar and Reuel Shinnar. The effects of the criminal justice system on the control of crime: A quantitative approach. *Law & Society Review*, 9(4):581–611, 1975.

Wesley Skogan and Kathleen Frydl. *Fairness and Effectiveness in Policing: the Evidence*. Committee on Law and Justice, Division of Behavioral and Social Sciences and Education. Washington DC: National Academies Press, 2004.

Richard Thaler. An econometric analysis of property crime. *Journal of Public Economics*, 8:37–51, 1977.

Kenneth I. Wolpin. An economic analysis of crime and punishment in england and wales, 1894-1967. *Journal of Political Economy*, 86(5):pp. 815–840, 1978. ISSN 00223808.

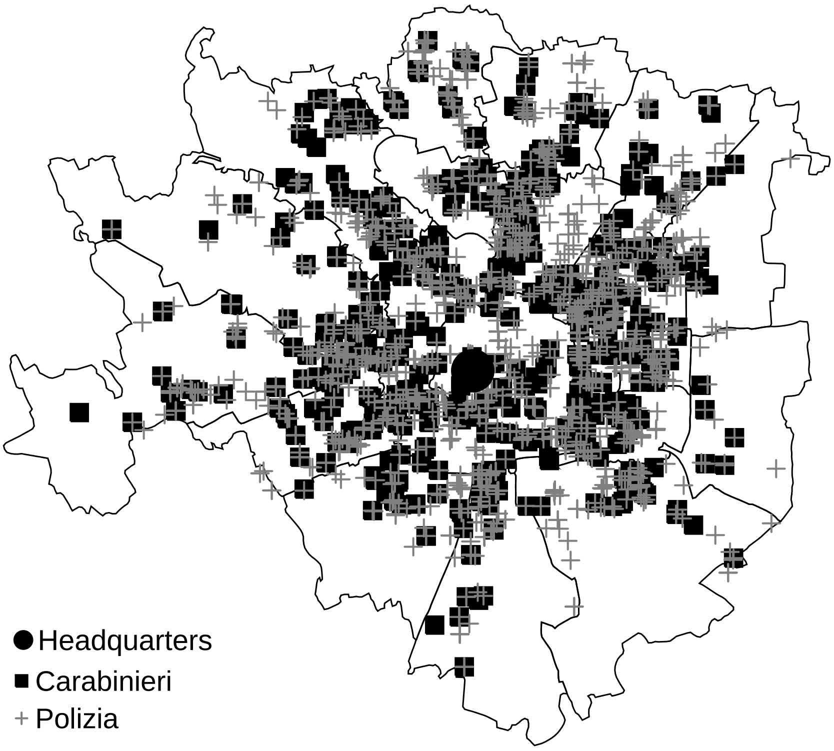

Figure 1: Headquarters' location

Notes: The black dot indicates where the Polizia and the Carabinieri headquarters are located. The squares and crosses indicate the location of robberies assigned to the two forces.

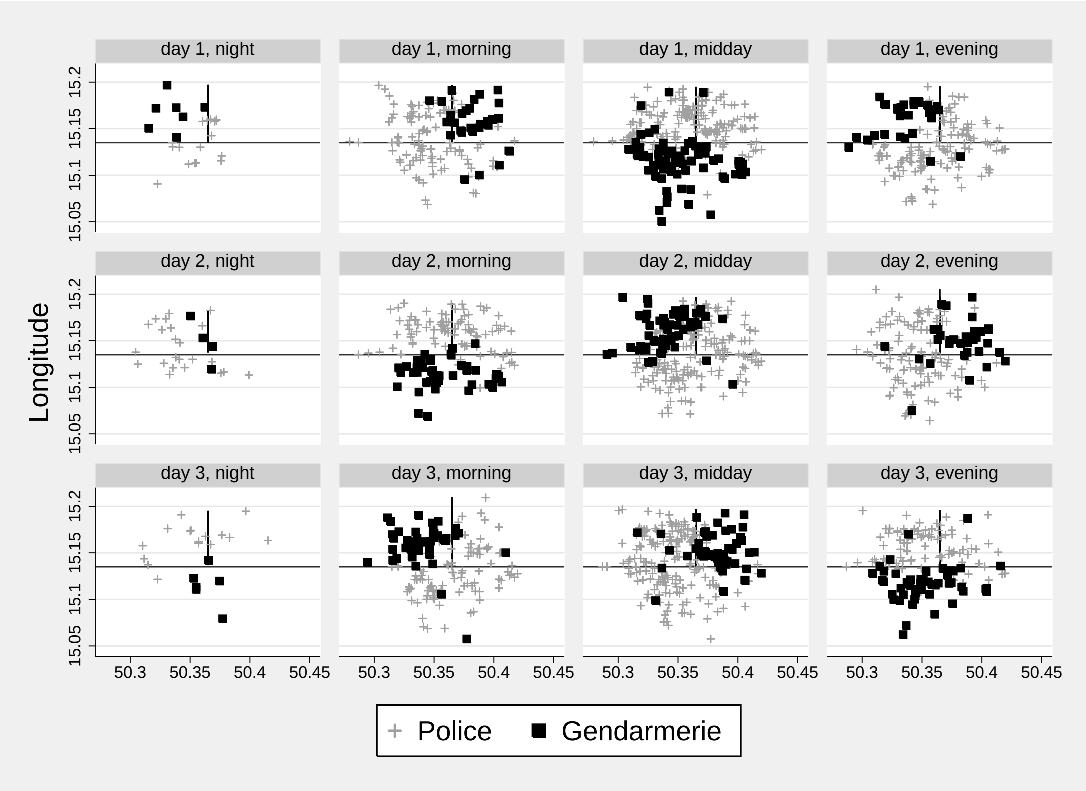

Figure 2: Geographic Distribution of Robberies by Group

Notes: Groups are defined based on the exact day and time of a robbery. Coordinates use Gauss-Boaga projections.

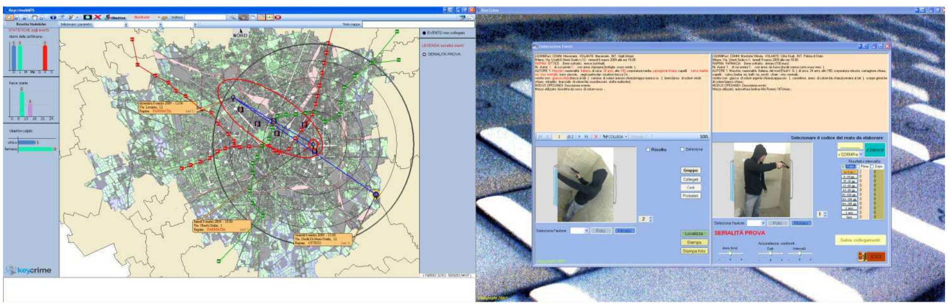

Figure 3: Comparison of Events

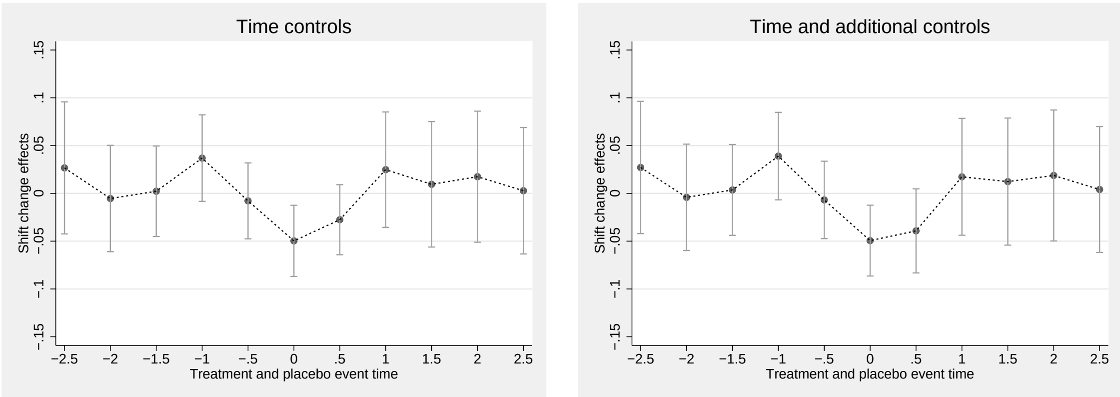

Figure 4: Shift Change Treatment and Placebo Effects on Clearance Rates

Notes: Each dot represents a different coefficient, and the corresponding vertical lines the 95 percent confidence intervals (based on clustered, by series, standard errors). Event time measures the time (in hours) from shift changes ranging from -2.5 hours to +2.5 hours. The estimate corresponding to the event time 0 corresponds to the correct shift change (centered at 12 am, 7 am, 1 pm, 7 pm). There is one estimate for each placebo (event time $\neq 0$) shift change shifted by 30 minutes forward or backward. All estimates control for a cubic Fourier series, while the right panel controls for the shops' closing time dummies.

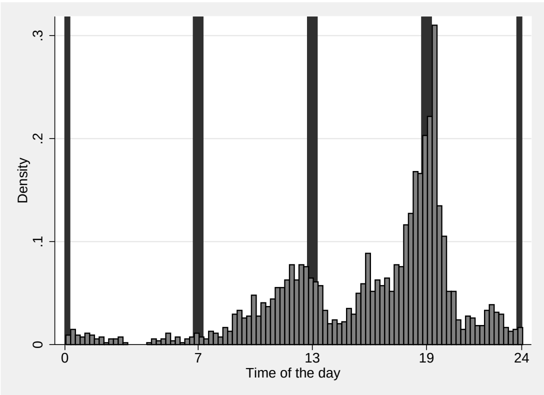

Figure 5: Distribution of Robberies

Notes: The histogram uses 15 minute bins. The darker vertical intervals indicate the half-hour shift change periods around shifts.

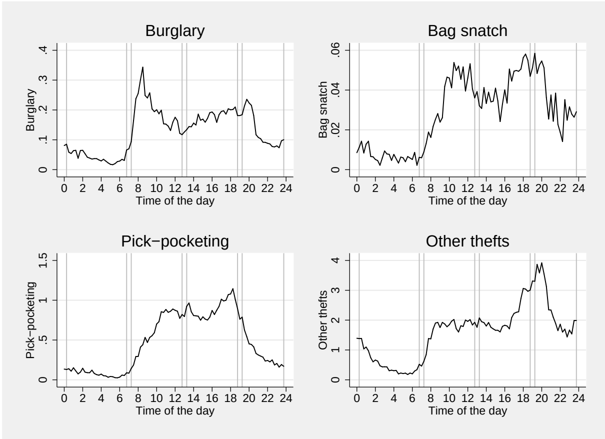

Figure 6: Average Number of Daily Thefts in 15 Minute Intervals

Notes: Based on 93 percent of all thefts that occurred in in Milan between 2009 and 2010. The series has been smoothed to reduce heaping. Data about reported thefts have been provided to *Transcrime* (Joint Research Centre on Transnational Crime) by the *Servizio Analisi Criminale* (Crime Analysis Department) of the Italian Ministry of the Interior within the framework of the project "Crime in Metropolitan Areas." Vertical lines indicate the half-hour shift change periods around shifts.

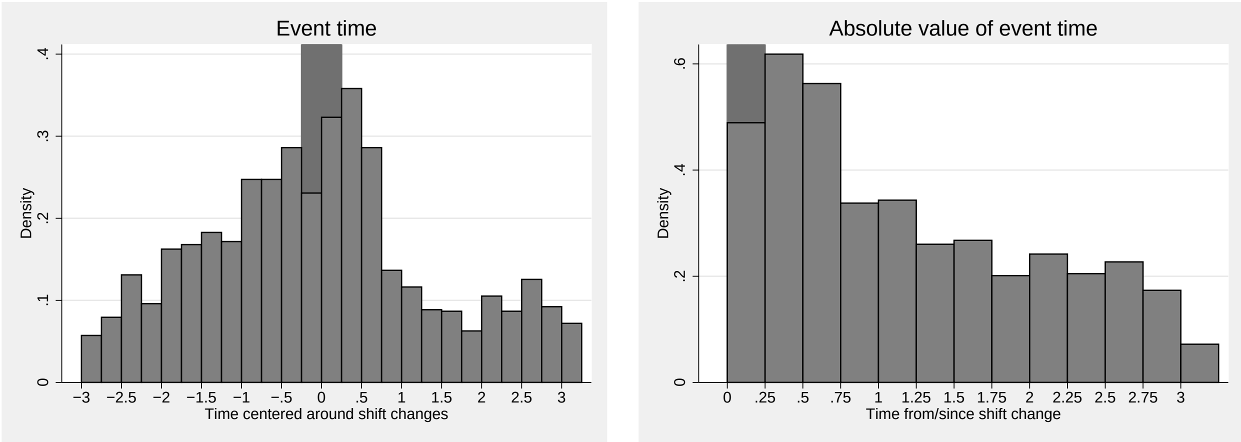

Figure 7: Distribution of Event Time and Absolute Value of Event Time

Notes: Event time measures the time (in hours) from shift changes ranging from -3 hours to +3 hours. The absolute value of event time is shown in the right panel. Histograms use 15 minute bins. The darker vertical intervals indicate the half-hour shift change periods around shifts.

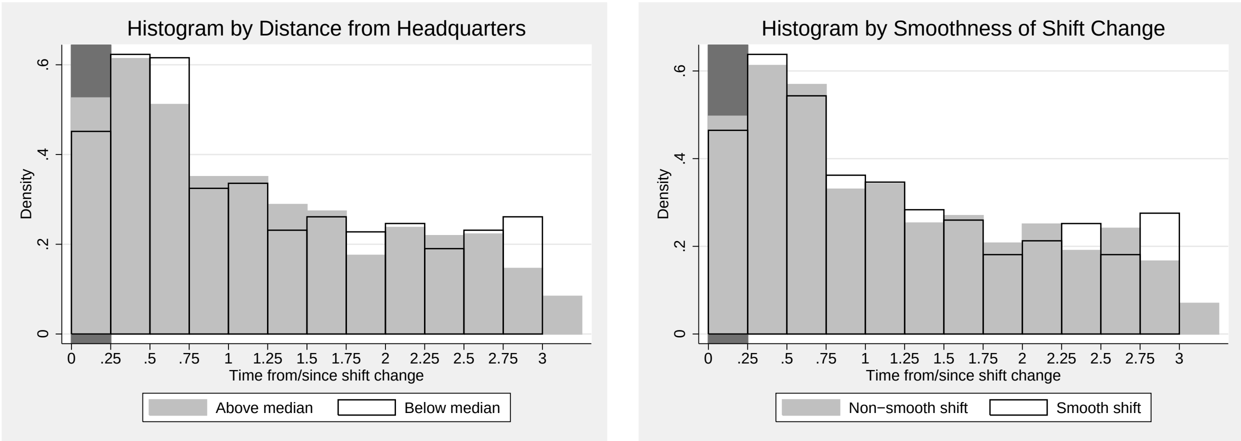

Figure 8: Absolute Value Event Time Histograms by Distance from Headquarters and by Smoothness of the Shift Change

Notes: Histograms use 15 minute bins. The darker vertical intervals indicate the half-hour shift change periods.

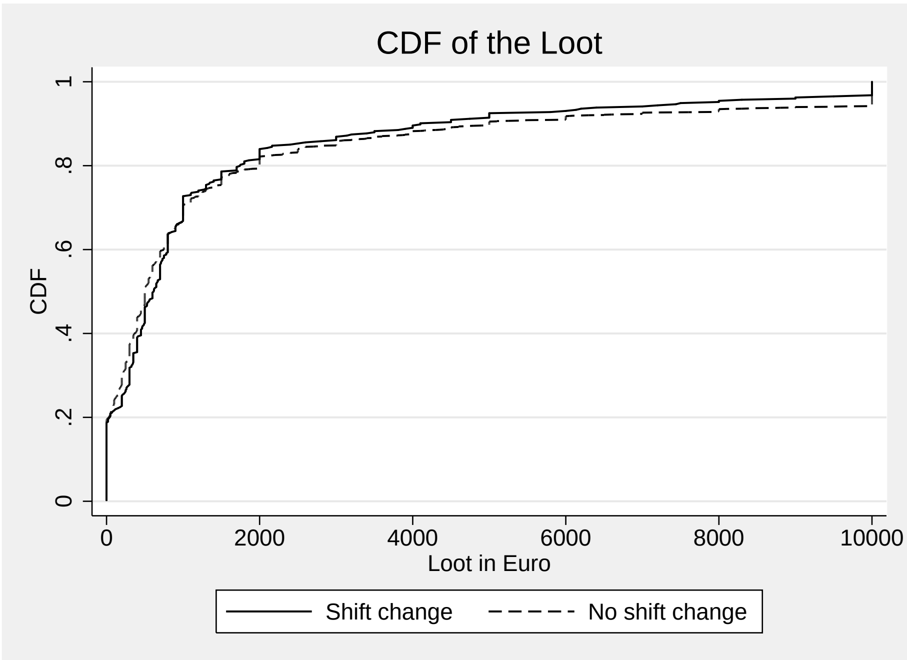

Figure 9: Cumulative Distribution of the Loot

Notes: The sample is based on robberies that happen within 1 hour and 15 minutes from the shift changes. The loot has been truncated at €10,000. The p-value of the two-sample Kolmogorov-Smirnov test for equality of distribution functions without truncation is 16.7 percent.

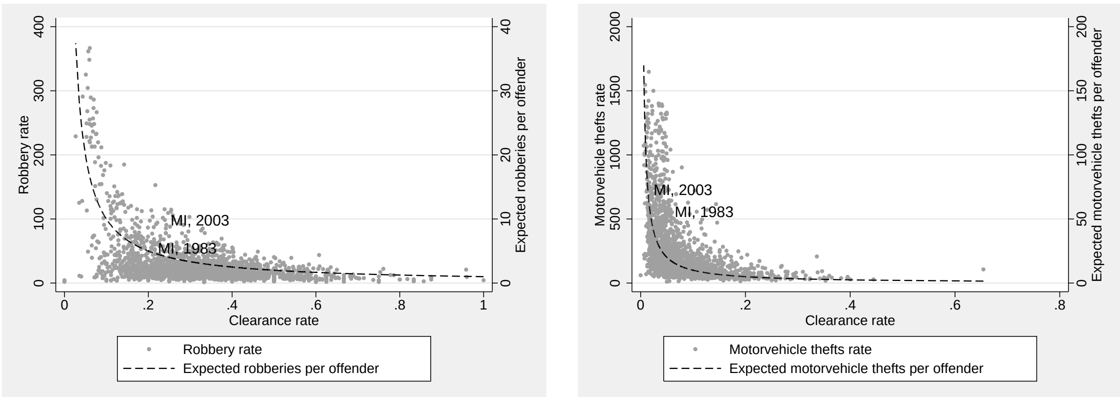

Figure 10: Aggregate Robbery Rates and MV Theft Rates vs. Their Clearance Rates

Notes: The dashed line simply plots $1/c$. Based on 103 Italian provinces between 1983 and 2003.

Table 1: Summary statistics

Variable	Shift change				Difference	
	Yes		No			
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Err.
Cleared robbery	0.091	0.288	0.148	0.355	-0.057	0.019***
Number of the series	6.048	8.106	4.916	6.605	1.133	0.498
Amount stolen in euros	2814.365	12335.651	2862.969	10950.471	-48.604	966.598
Average age	26.616	11.777	26.558	12.599	0.058	0.720
Ages are unknown	0.085	0.279	0.104	0.306	-0.019	0.018
Firearm 0/1	0.258	0.438	0.224	0.417	0.033	0.030
At least one knife, but no firearm	0.110	0.314	0.089	0.285	0.021	0.019
Number of robbers	1.592	0.647	1.567	0.729	0.025	0.042
Some Italian	0.799	0.401	0.786	0.410	0.013	0.026
Shops' closing time 0/1 (90th percentile)	0.102	0.303	0.178	0.383	-0.076	0.020***
Shops' closing time 0/1 (maximum)	0.048	0.214	0.088	0.283	-0.039	0.015***
Polizia (Police) 0/1	0.745	0.436	0.730	0.444	0.015	0.026
Serial robbers	0.629	0.484	0.574	0.495	0.055	0.031
Predictive policing (*Keycrime*)	0.249	0.433	0.234	0.424	0.015	0.027
Southern area	0.428	0.495	0.436	0.496	-0.008	0.030
North-Western area	0.334	0.472	0.350	0.477	-0.015	0.029
Year	2009.246	1.030	2009.239	1.021	0.008	0.064
Month	6.074	3.800	5.838	3.698	0.236	0.235
Day of the week	3.278	1.921	3.228	1.809	0.050	0.112
Distance from the headquarters (in minutes)	14.762	4.095	14.246	4.457	0.516	0.276
Distance from the headquarters (in kilometers)	6.024	2.134	5.756	2.275	0.268	0.148
N. obs.	353		1,814			

Table 2: Simple Difference in Clearance Rates

	Clearance rate	$\delta = (1) - (0)$	se(δ)	N.obs
	Panel A: Clearance rates by turnover			
No turnover (0)	0.148			1814
Turnover (1)	0.091	-0.057	0.019	353
	Panel B: Clearance rates across turnovers			
No turnover (0)	0.148			1814
Morning turnover, 7am (1)	0.000	-0.148	0.037	11
Midday turnover, 12pm (1)	0.104	-0.044	0.021	77
Evevning turnover, 7pm (1)	0.085	-0.063	0.021	247
Night turnover, 12am (1)	0.167	0.019	0.090	18
Total				2167

Notes: Linear probability model of clearing the case with clustered (by series) standard errors ($se(\delta)$). There are no controls other than the constant term and the shift change dummy.

Table 3: Event Time Study of Clearance Rates

	(1)	(2)	(3)
	Cleared Robbery (0/1)		
30 min. shift change interval (SCI)	-0.045**	-0.050**	-0.044**
	(0.021)	(0.021)	(0.021)
30 min. SCI shifted by +1.5h	0.013	0.007	0.004
	(0.038)	(0.038)	(0.037)
30 min. SCI shifted by -1.5h	0.032	0.027	-0.022
	(0.040)	(0.040)	(0.042)
30 min. SCI shifted by +2h	0.051*	0.048	0.009
	(0.030)	(0.030)	(0.033)
30 min. SCI shifted by -2h	-0.004	-0.011	-0.021
	(0.028)	(0.029)	(0.030)
30 min. SCI shifted by +2.5h	0.014	0.007	-0.009
	(0.033)	(0.033)	(0.034)
30 min. SCI shifted by -2.5h	0.043	0.037	0.009
	(0.034)	(0.035)	(0.035)
Shops' closing time 0/1 (90th percentile)		-0.029	-0.028
		(0.021)	(0.023)
Shops' closing time 0/1 (maximum)		0.011	0.026
		(0.029)	(0.030)
Other Xs	No	No	Yes
Constant	0.136***	0.143***	0.311***
	(0.011)	(0.013)	(0.072)
Observations	2167	2167	2167
R-squared	0.006	0.007	0.062

Notes: Linear probability model of clearing the case with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The SCI dummy variable is equal to one if the robbery happened in the following time intervals: 6.45am-7.15am, 12.45pm-1.15pm, 6.45pm-7.15pm, 11.45pm-12.15am. The excluded time period is the 1h15min period preceding and 1h15min following the SCI. The other Xs are the value of the stolen loot, a police dummy, a dummy for robbers with some experience, the predictive policing dummy, a south and a north-west dummy, year by month dummies, day of the week dummies, age, age squared, a dummy when age is missing, a firearm dummy, a knife dummy, the number of perpetrators, and whether some of the robbers appeared to be Italian.

Table 4: Clearance Rate Regressions Controlling for Semi-parametric Functions of Time

	(1)	(2)	(3)	(4)	(5)	(6)
	Cleared Robbery (0/1)					
	Fourier series		Quartic in time		Cubic spline	
Shift change 0/1	-0.050***	-0.049***	-0.051***	-0.052***	-0.043**	-0.041**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Constant	0.158***	0.158***	0.156*	0.154*	0.158*	0.158*
	(0.013)	(0.013)	(0.080)	(0.080)	(0.085)	(0.085)
Shops closing FE	No	Yes	No	Yes	No	Yes
Observations	2167	2167	2167	2167	2167	2167
R-squared	0.010	0.010	0.008	0.008	0.011	0.011

Notes: Linear probability model of clearing the case with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The Fourier series contains 2 sine and 2 cosine terms (the optimal size based on cross-validation) and the cubic splines is based on 7 equally distanced knots. Online Figure 12 shows the unconditional smoothed function $f(t)$.

Table 5: Heterogeneity by Distance from the HQs and Shift Change Type

	(1)	(2)	(3)	(4)
	Cleared Robbery (0/1)			
Shift change int. above median distance from the HQ	-0.077***	-0.073**		
	(0.028)	(0.032)		
Shift change int. below median distance from the HQ	-0.002	-0.009		
	(0.027)	(0.029)		
Below median time from Police HQ	-0.035**	-0.024		
	(0.016)	(0.023)		
Non-smooth Shift change period			-0.039*	-0.038
			(0.022)	(0.025)
Smooth Shift change period			-0.050	-0.062
			(0.040)	(0.043)
Smooth shift change 0/1			0.012	0.028
			(0.020)	(0.027)
Other Xs	Yes	Yes	Yes	Yes
Fourier series	Yes	No	Yes	No
30' Event time dummies	No	Yes	No	Yes
Observations	2167	2167	2167	2167
p-value for the difference between the shift change effects	0.0532	0.137	0.819	0.633
R-squared	0.067	0.066	0.064	0.066

Notes: Linear probability model of clearing the case with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. All regressions control for the same regressors used in Column 3 of Table 3. Fourier regressions control for 2 sine and 2 cosine functions of time, while the Event time regressions control for 12 interacted 30 minute event time dummies.

Table 6: Individually Defined Shift change Period

	(1)	(2)	(3)	(4)
	Cleared Robbery (0/1)			
Turnover effects with	Fourier		'$\pm 1h15m$'	
$\kappa = 10/10$	-0.051***	-0.050***	-0.046**	-0.051**
	(0.019)	(0.019)	(0.021)	(0.022)
$\kappa = 11/10$	-0.054***	-0.054***	-0.050**	-0.054***
	(0.019)	(0.019)	(0.021)	(0.021)
$\kappa = 12/10$	-0.057***	-0.056***	-0.054***	-0.058***
	(0.018)	(0.018)	(0.020)	(0.020)
$\kappa = 13/10$	-0.056***	-0.055***	-0.052***	-0.056***
	(0.017)	(0.017)	(0.019)	(0.020)
$\kappa = 14/10$	-0.048***	-0.047***	-0.044**	-0.047**
	(0.017)	(0.017)	(0.019)	(0.019)
$\kappa = 15/10$	-0.049***	-0.048***	-0.046**	-0.049***
	(0.016)	(0.017)	(0.018)	(0.019)
Other Xs	No	Yes	No	Yes
Observations	2167	2167	1316	1316

Notes: Each coefficient measures the effect of a shift change period and refers to a different regression. These estimates exploit information on the exact location of the incident, and Google's predicted duration τ of driving from the *Carabinieri* or the *Polizia* headquarters to such location. Given that Google's estimated durations for Italy do not take traffic into account one can multiply such number by a constant that is larger or equal to 1: $Y_{i,n} = \alpha + \delta I(|t_{i,n} - T| \leq \kappa\tau_{i,n}) + f(t_{i,n})\epsilon_{i,n}$. Fourier regressions control for 2 sine and 2 cosine functions of time, while the $\pm 1h15m$ regressions use only robberies that happen within 1 hour and 15 minutes from the shift changes (in line with the event study dummies). Linear probability model of clearing the case with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Spillovers

	(1)	(2)	(3)
	Cleared Robbery (0/1)		
	Fourier		
Shift change 0/1	-0.073***		
	(0.022)		
Individual shift change $\kappa = 12/10$		-0.078***	
		(0.022)	
30 min. shift change interval (SCI)			-0.073***
			(0.024)
30 min. SCI shifted by +1.5h			0.052
			(0.054)
30 min. SCI shifted by +2h			0.045
			(0.050)
30 min. SCI shifted by +2.5h			0.031
			(0.037)
30 min. SCI shifted by -1.5h			-0.006
			(0.041)
30 min. SCI shifted by -2h			0.009
			(0.043)
30 min. SCI shifted by -2.5h			0.017
			(0.039)
Constant	0.163***	0.164***	0.148***
	(0.016)	(0.016)	(0.017)
Observations	1,297	1,297	1,297
R-squared	0.013	0.014	0.010

Notes: For each day and for each police force the sample is restricted to the very "first" robbery. See Table 3 for a description of the regressors. Subsequent robberies are excluded. The Fourier regressions control for 2 sine and 2 cosine functions of time. Linear probability model of clearing the case with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Number of Robberies

	(1)	(2)	(3)	(4)
	Number of Robberies			
30 min. shift change interval (SCI)	0.401**	0.220	0.500***	0.292**
	(0.193)	(0.280)	(0.137)	(0.140)
30 min. SCI shifted by +1.5h		-0.943***		-0.829***
		(0.190)		(0.141)
30 min. SCI shifted by -1.5h		-0.228		-0.218*
		(0.163)		(0.118)
30 min. SCI shifted by +2h		-0.591***		-0.568***
		(0.192)		(0.149)
30 min. SCI shifted by -2h		-0.296*		-0.438***
		(0.170)		(0.125)
30 min. SCI shifted by +2.5h		-0.419**		-0.272**
		(0.172)		(0.109)
30 min. SCI shifted by -2.5h		-0.678***		-0.513***
		(0.215)		(0.142)
Intervals interacted with:	Above Median Distance from HQ		Smooth Changover	
Shift change interval (SCI)	0.166	0.158	-0.036	-0.035
	(0.219)	(0.362)	(0.219)	(0.229)
SCI shifted by +1.5h		-0.111		-0.269
		(0.251)		(0.269)
SCI shifted by -1.5h		0.031		0.057
		(0.221)		(0.194)
SCI shifted by +2h		-0.440		-0.294
		(0.269)		(0.280)
SCI shifted by -2h		-0.354		-0.018
		(0.236)		(0.225)
SCI shifted by +2.5h		-0.130		-0.090
		(0.225)		(0.208)
SCI shifted by -2.5h		0.363		0.328
		(0.280)		(0.241)
Above median distance from HQ	0.002	0.042		
	(0.066)	(0.121)		
Smooth Changeover			-0.013	-0.003
			(0.070)	(0.097)
Constant	-0.434***	0.473***	-0.429***	-0.192***
	(0.068)	(0.095)	(0.060)	(0.066)
Fourier series	Yes	No	Yes	No
Within 1h15min from SC	No	No	No	No
Observations	1,656	1,656	1,656	1,656

Notes: Poisson model of the number of robberies aggregated by 30 minute periods, by area (north-east, north-west, south), by median distance from the headquarters (HQ), and by shift change day type (from 1 to 3). Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. See Table 3 for a description of the regressors.

Table 9: Balance Tests

	Simple Differences			
	Fourier		'$\pm 1h15min$'	
	$\widehat{\delta}$	$se(\widehat{\delta})$	$\widehat{\delta}$	$se(\widehat{\delta})$
Loot in €1,000	0.091	0.681	0.075	0.720
Average age	-0.114	0.803	0.189	0.813
Ages are unknown	-0.009	0.019	-0.017	0.018
Firearm 0/1	0.049	0.031	0.052	0.031
At least one knife, but no firearm	0.007	0.015	0.007	0.015
Number of robbers	0.065	0.044	0.077	0.043
Some Italian	-0.003	0.025	0.011	0.025
Shops' closing time 0/1 (90th percentile)	-0.161	0.024***	-0.118	0.022***
Shops' closing time 0/1 (maximum)	-0.121	0.018***	-0.080	0.016***
Police 0/1	0.010	0.026	0.017	0.025
Southern area	-0.069	0.029	-0.055	0.029
North-Western area	-0.041	0.030	-0.037	0.028
	Difference-in-Differences Based on Distance			
Loot in €1,000	-1.131	2.150	-0.296	2.171
Average age	3.012	1.395**	3.279	1.372**
Ages are unknown	-0.052	0.033**	-0.052	0.032
Firearm 0/1	-0.029	0.052	-0.005	0.053
At least one knife, but no firearm	-0.051	0.036	-0.073	0.035**
Number of robbers	-0.115	0.077	-0.124	0.075*
Some Italian	0.050	0.047	0.068	0.045
Shops' closing time 0/1 (90th percentile)	0.088	0.046*	0.088	0.037**
Shops' closing time 0/1 (maximum)	0.049	0.035*	0.036	0.027
Police 0/1	0.087	0.054	0.030	0.051
Southern area	-0.032	0.058	-0.022	0.057
North-Western area	-0.022	0.062	-0.012	0.059

Notes: Each row corresponds to a different linear regression with the dependent variable listed on the left. The simple difference is the coefficient on the shift change dummy. The difference-in-difference is the coefficient on the interaction between the shift change dummy variable and the Above Median distance dummy variable. Fourier regressions control for 2 sine and 2 cosine functions of time, while the $\pm 1h15m$ regressions use only robberies that happen within 1 hour and 15 minutes from the shift changes (in line with the event study dummies). *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Recurrence and Clearance

Number of the series	Cleared robbery No	Cleared robbery Yes	Clearance rate	Recurrence rate estimate	Recurrence rate upper bound	Recurrence rate lower bound
1	771	136	0.15	-		-
2	215	29	0.12	0.32	0.42	0.27
3	153	23	0.13	0.82	0.84	0.72
4	111	19	0.15	0.85	0.87	0.74
5	91	8	0.08	0.89	0.91	0.76
6	77	7	0.08	0.92	0.93	0.85
7	64	8	0.11	0.94	0.94	0.86
8	53	5	0.09	0.91	0.92	0.81
9	44	5	0.10	0.92	0.93	0.84
10	39	4	0.09	0.98	0.98	0.88
11	32	4	0.11	0.92	0.93	0.84
12	29	3	0.09	1.00	1.00	0.89
13	24	5	0.17	1.00	1.00	0.91
14	21	1	0.05	0.92	0.93	0.76
15	20	0	0.00	0.95	0.95	0.91
16	17	2	0.11	0.95	0.95	0.95
17	17	0	0.00	1.00	1.00	0.89
18	13	3	0.19	0.94	0.94	0.94
19	11	2	0.15	1.00	1.00	0.81
20	10	1	0.09	1.00	1.00	0.85

Notes: The sample starts with 907 disjoint group of robbers performing a robbery. Of these robberies 136 are cleared immediately (15 percent). Based on the remaining 771 groups given that 244 perform a second robbery, the recurrence rate is 32 percent. Depending on what one assumes about the recurrence of the 136 groups who were arrested after the first robbery one can compute upper and lower bounds of the recurrence rate.

A For Online Publication: Appendix

A.1 Optimal choice of k

To avoid overfitting one can either use the Akaike Information Criterion, which penalizes the likelihood function increasingly as more and more sine and cosine terms are added, or cross-validation, which rests on out of sample predictions. In particular, to predict the outcome of observation i one uses all the other $N-1$ observations, repeating the exercise for all N observations.[71] Table 13 shows that using this simple but slow "leave-one-out" cross-validation method, $k = 2$ minimizes the cross-validation mean squared as well as the AIC objective function.

A.2 Optimal timing of shift changes

If robberies were the only crime, one would like to have shift changes when most businesses are closed and robberies are rare. The fraction of robberies that fall within a 30 minute shift change period can be drastically reduced from about 15 to about 2.5 percent by deferring all shift changes by just one and a half hours (1.30am, 8.30am, 2.30pm, 8.30pm). One can estimate that the corresponding reduction in the expected number of robberies would be close to 6 percent. The change is small but could become much larger if criminals started exploiting these inefficiencies.[72]

B Additional Tests for Deterrence

B.1 Correlation between ability and shift change targeting

The first two tests use very detailed information on the timing of the robbery but no information about their evolution. Exploiting the panel structure of the data delivers additional tests for selection. These tests are designed to look for evidence of learning,

[71] See (Newey et al., 1990) for a similar application of cross-validation.

[72] Such change is equal to $\sum_{\tau=1}^{\infty} p_{t,1}^{\tau} - \sum_{\tau=1}^{\infty} p_{t,0}^{\tau}$, where $p_{t,i} = 0.865 + 0.05I(|t - T_i| \leq 15)$ represents the probability of success of a robbery, which depends on whether the robbery happened during a shift change period (the expected number of robberies for recurrent robbers, meaning robbers who will not stop robbing banks until caught, when their likelihood of success is p is $\sum_{\tau=1}^{\infty} p^{\tau}$). Postponing the shift changes by 1.5 hours lowers the probability $P(|t - T_i| \leq 15)$ from 15 percent to 2.5 percent, which can be gauged using Table 7. For recurrent criminals the expected number of robberies would drop from 6 to 5.6. Given that there are about 260 first time robbers each year and that 1/3 of these are recurrent offenders the reduction in the number of crimes per year would be close to 40. Since the average haul is close to €2,900, one would reduce the total haul by about €100,000 a year.

testing whether at least *some* robbers systematically or at least after some time target business during shift change periods.

One should expect more able robbers to be more likely to target businesses during shift change periods, and robbers who learn about any disturbance to the patrolling due to shift changes should become more and more likely to target such periods. The previous section has shown that variables that related to ability do not vary during shift changes, but the longitudinal aspect of the data allows one to measure ability in a different way. Recurrent robbers tend to be successful when they manage to behave unpredictably, limiting the effectiveness of *predictive policing*. Probably the most prominent unpredictability factor is the location of the robbery. Robbers who tend to choose business that are located close to each other are more likely to be caught. This can clearly be seen in the first panel of Figure 17. The Figure plots, for each of the 244 groups of robbers who performed at least 2 robberies, the total number of performed robberies against the average distance between subsequent robberies. Keeping in mind that recurrent robbers tend to rob businesses until they get caught the total number of business they manage to rob is a good proxy for their rate of success. Success is clearly positively correlated with the average distance between subsequent robbed businesses. Regressing the total number of robberies on the average distance one gets a coefficient equal to 0.53 with a standard error of 0.25. Given that the average distance is equal to 2.45 km (1.5 miles) and the standard deviation is 1.63 km (1 mile), adding a standard deviation to the average distance increases success by almost an additional robbery.[73]. Regressing the total number of robberies on the fraction of robberies that were done during shift change periods one again gets a coefficient which is positive and significant. A standard deviation increase (0.20) in the fraction of robberies performed during shift change periods has almost the same effect as a standard deviation increase in the average distance. If choosing a shift change and choosing the distance between targets were deliberate choices and were both signaling a higher degree of ability, one would expect the two measures to be correlated with each other. Panel 3 of Figure 17 shows that this is not the case. The regression line is flat and if anything has a negative slope.[74]

[73]Running a log-log regression the estimated elasticity is significantly different from 0 and larger than 20 percent.

[74]Inverting the regression the results are the same, there is no significance and the slope is negative.

B.2 Learning about shift changes

It could still be that robbers learn over time about the opportunities that arises during shift change. If this were the case one would expect these robbers to start targeting such periods. The easiest way to see this is to observe the evolution of the time chosen by the individual offenders across robberies. The 9 panels of Figure 19 show the evolution of the time chosen by the 9 most prolific groups of robbers.[75] Not only is there little evidence of convergence (learning), but for 7 out of 9 most prolific offenders less than one in three robbery falls inside a turnover period (individually defined as in Table 6 with $\kappa = 1.2$).

In order to see whether the persistence in the chosen time of the day that is visible around shift changes represents an anomaly, one can estimate whether the probability of organizing a robbery during an event time period depends on having organized the previous robbery during the same event time period. Using once again a linear probability model, I regress the event time dummy $\Gamma^c_{i,n}$ on the event time dummy in the previous robbery $\Gamma^c_{i,n-1}$. Given the autoregressive nature of the regression I do not control for the Fourier series, but in line with the event studies, I select the sample to be within 1 hour and 15 minutes around the chosen event time. Figure 18 shows that the shift changes (event time 0) do not show autoregressive coefficients that are any different from the other event times.

Finally, another simple way to directly test whether the results are driven by selection is to compute the shift change effect on the sample of offenders who have never before organized a robbery during a shift change. For these robbers a shift change effect is less likely to be the product of ability. Table 14 shows that there is no evidence that with this sample selection the shift change effects disappear, no matter whether the shift change periods are computed using the 30 minute approximation, or they are computed using the individual information on the distance from the headquarters. This indicates that as long as for most robbers the learning is not sudden and discontinuous, selection does not explain the differences in clearance rates.

[75]The 9 groups of robbers organize about 15 percent of all robberies, and all the previous results are robust to the exclusion of these most prolific groups of robbers.

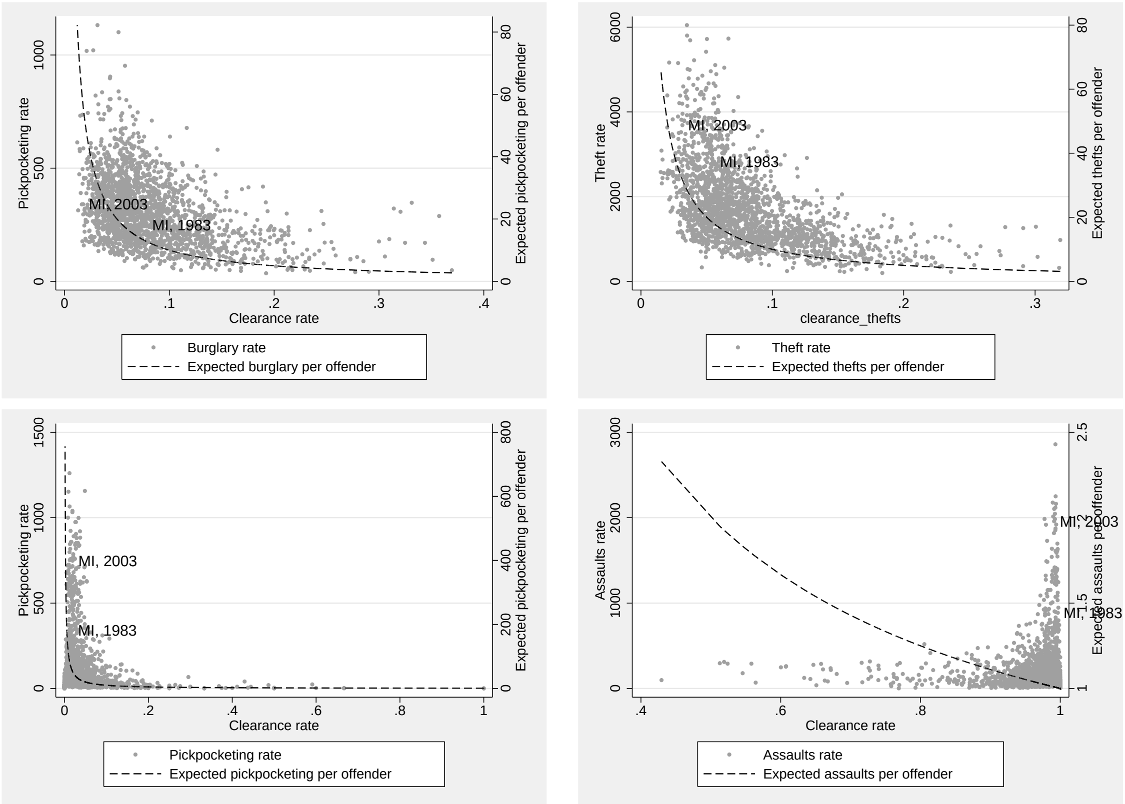

Figure 11: Aggregate Crime Rates and Their Corresponding Clearance Rates

Notes: The dashed line simply plots $1/c$. Based on 103 Italian provinces between 1983 and 2003.

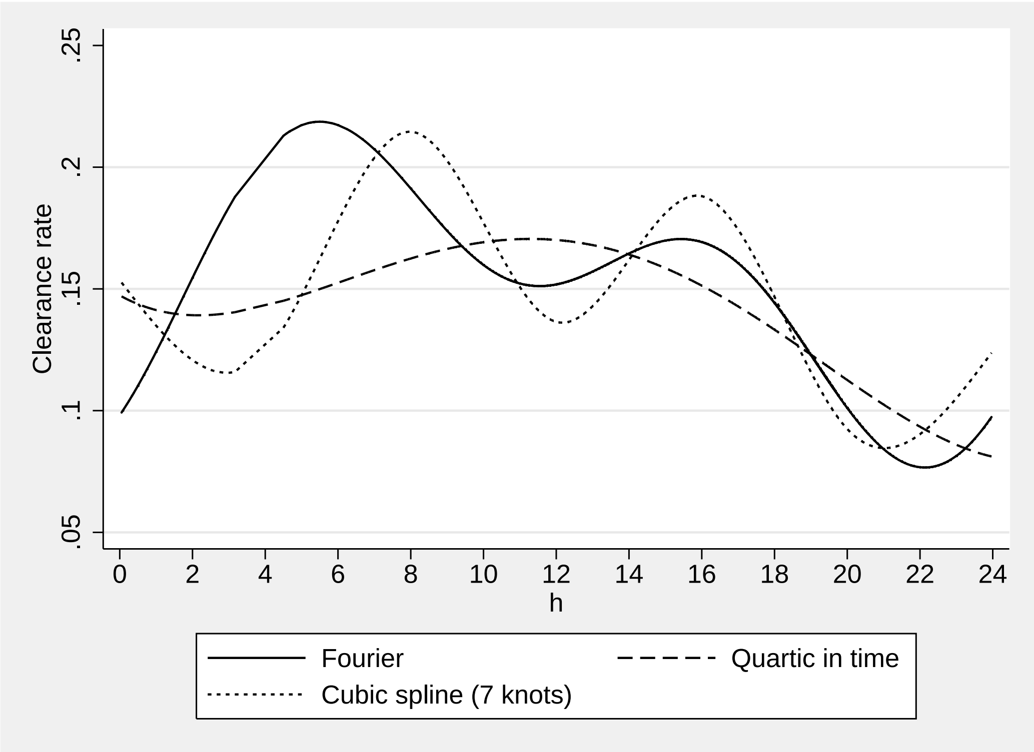

Figure 12: Predicted Clearance Rates

Notes: The figure shows smoothed clearance rates based on local mean smoothers with a bandwidth of one hour, Fourier series with 2 sine and 2 cosine terms (the optimal size based on cross-validation), cubic splines with 7 equally distanced knots, and a quartic polynomial in time.

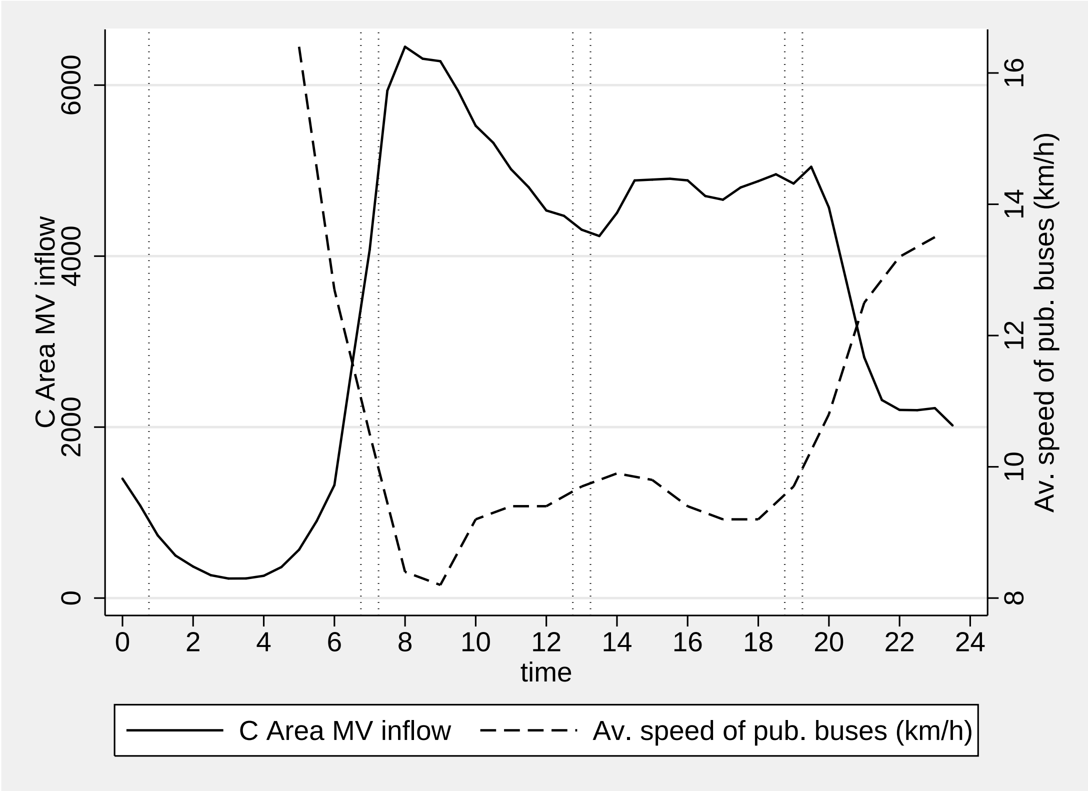

Figure 13: Traffic in Milan

Notes: The plot shows the average speed of public buses in the city center (right axis) and the inflow of cars in the city center (*Area C*, left axis). Source: http://www.amat-mi.it/.

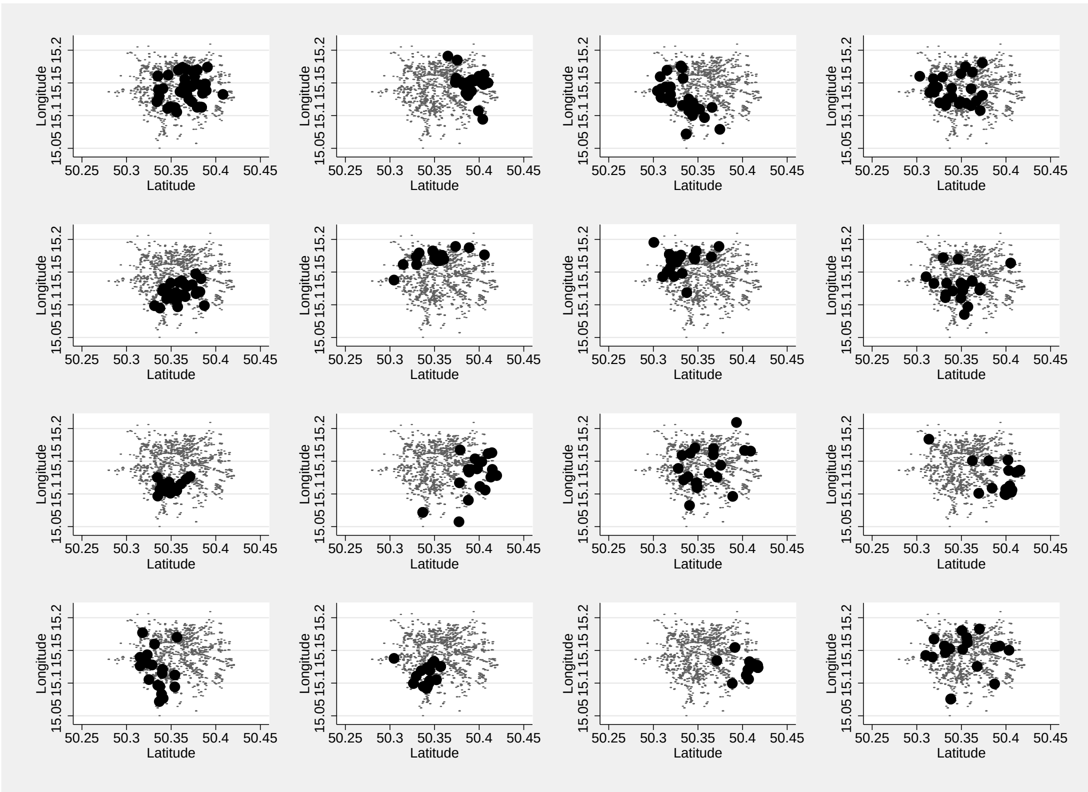

Figure 14: Geographic Distribution of Robberies by Criminal Group

Notes: The plots are restricted to those groups who performed at least 15 robberies. In each plot the large black dots indicate the chosen victims by a separate group of robbers. In order to visualize the degree of clustering, the small grey dots represent all the other robberies.

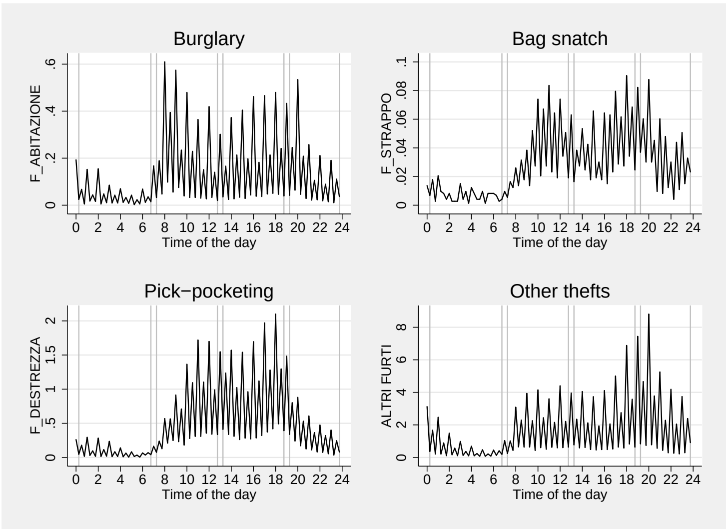

Figure 15: Average Number of Daily Thefts in 15 Minute Intervals

Notes: Based on 93 percent of all thefts that occurred in Milan between 2009 and 2010. This figure corresponds to Figure 6, but before smoothing the series to reduce heaping.

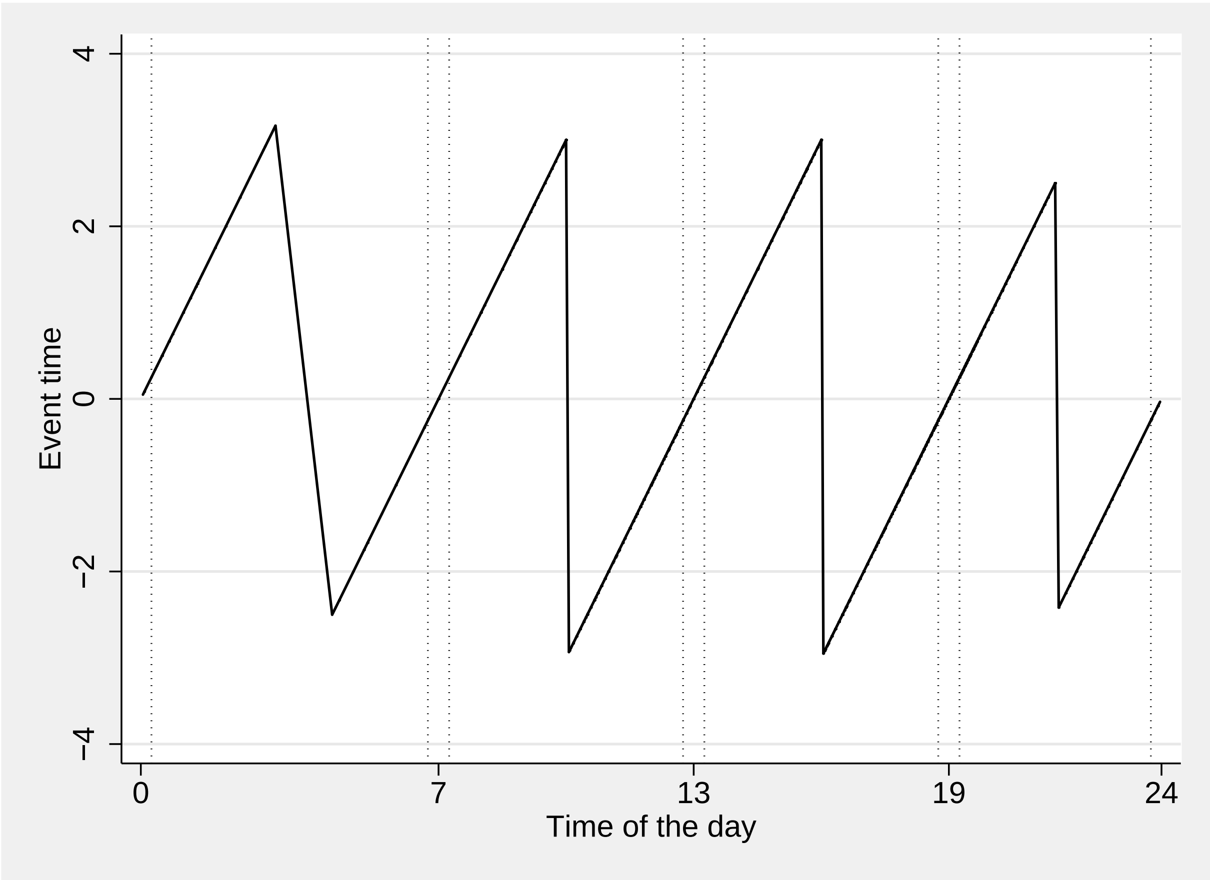

Figure 16: Event time vs. Time of the Day

Notes: The figures show the observed relationship between time of the day and event time.

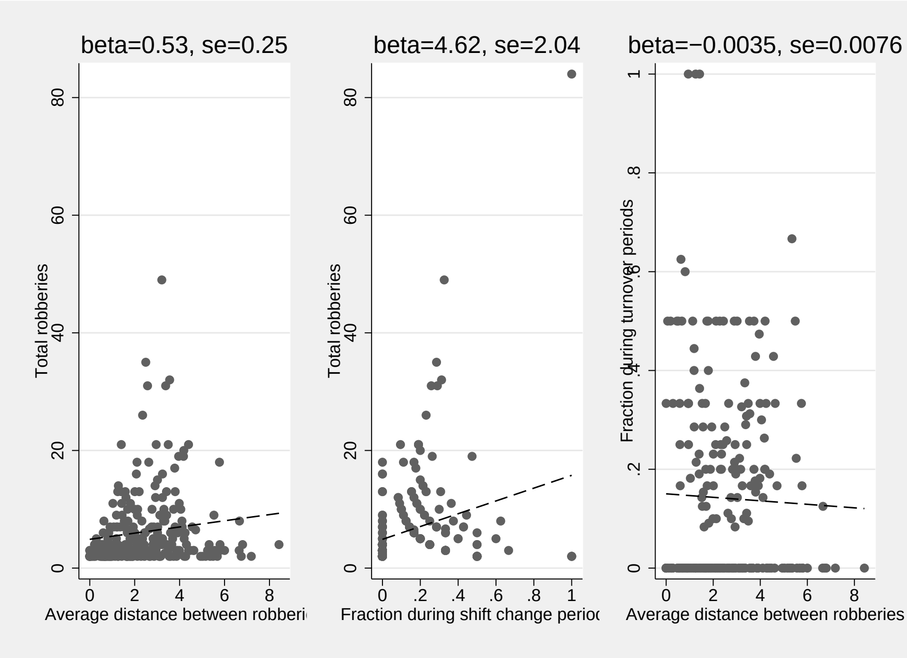

Figure 17: Unpredictability, Success, and Shift change Periods

Notes: Each plot is based on averages over 244 individual robbers or groups of robbers who performed at least two robberies. Distances are air travel distances in kilometers computed using Pythagoras theorem. The average distance is 2.45 km (sd= 1.64), the average total number of robberies is 6.15 (sd=6.34) and the fraction of shift change periods is 0.14 (sd=0.20).

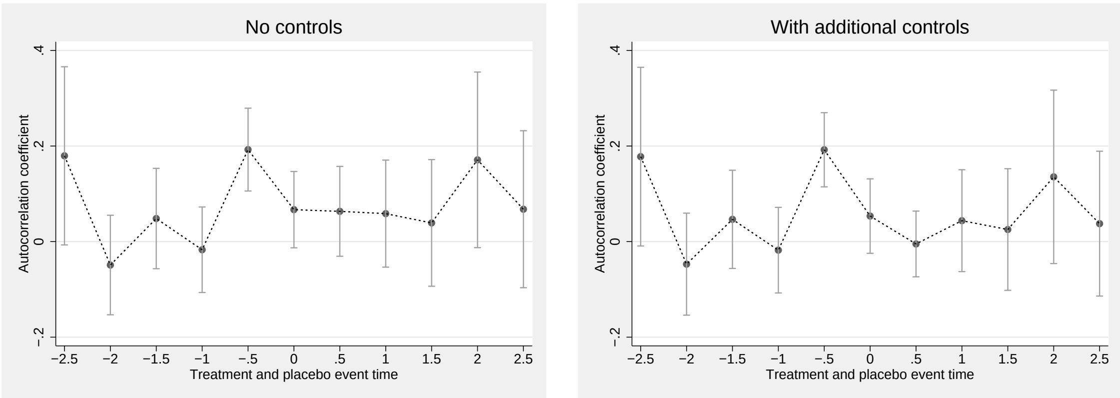

Figure 18: Autocorrelation of Treatment and Placebo Shift Changes

Notes: Each dot represents a different autocorrelation coefficient between selecting a shift change or a placebo shift change and having selected one in the previous robbery. The corresponding vertical lines measure the 95 percent confidence intervals (based on clustered, by series, standard errors). Event time measures the time (in hours) from shift changes ranging from -2.5 hours to +2.5 hours. The estimate corresponding to the event time 0 corresponds to the correct shift change (centered at 12 am, 7 am, 1 pm, 7 pm). There is one estimate for each placebo (event time $\neq 0$) shift change shifted by 30 minutes forward or backward. In line with the event study, each sample is restricted to 1 hour and 15 minutes before and after the shift change (placebo or real). The autocorrelation coefficients in the right panel are conditional on the shops' closing time dummies.

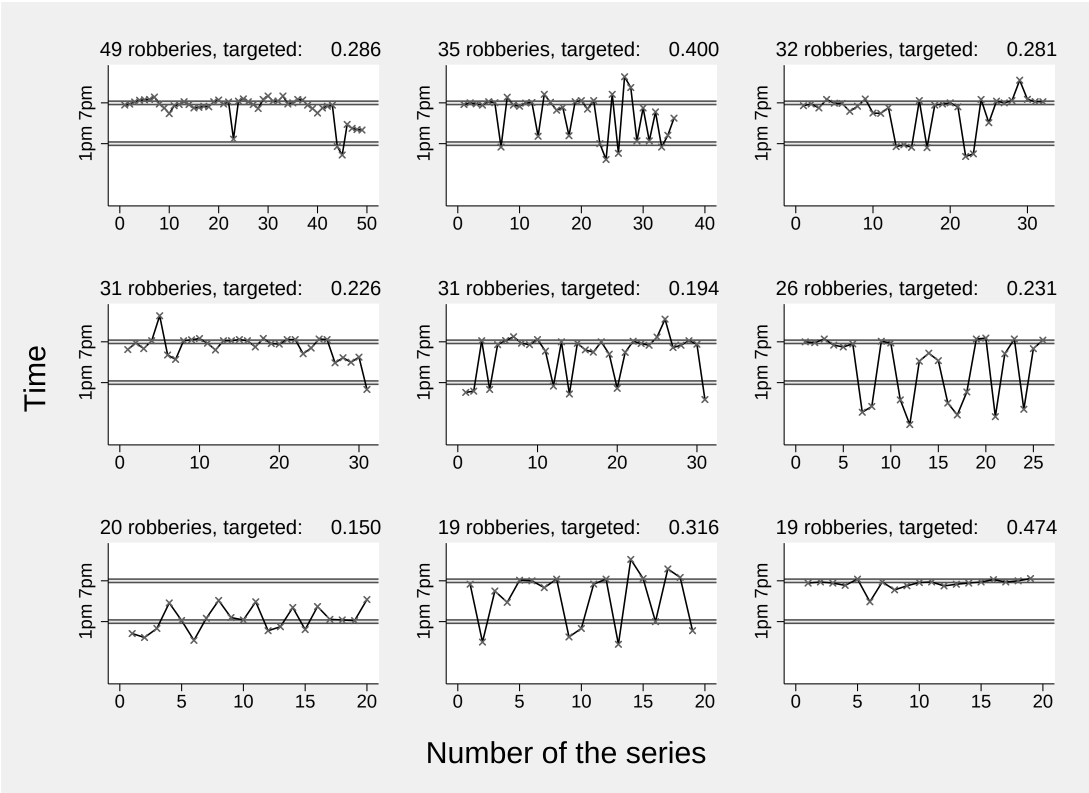

Figure 19: Individual Time Patterns

Notes: Horizontal lines indicate the 30 minute shift change periods around shifts.

Table 11: Closing Time of Businesses

	90th percentile	maximum	Freq.
Apparel shops	7:40pm	8:10pm	49
Betting shops	8:02pm	11:00pm	50
Travel agencies	7:45pm	7:45pm	10
Groceries	7:45pm	7:45pm	9
Others	8:00pm	11:45pm	202
Banks	3:45pm	6:10pm	237
Cafes	9:17pm	11:30pm	68
Gas stations	7:55pm	8:20pm	31
Newspaper stands	8:10pm	11:27pm	47
Estheticians	9:20pm	10:30pm	12
Pharmacies	8:00pm	11:55pm	763
Jewelers	6:32pm	7:17pm	24
Hotels	11:00pm	11:46pm	28
Bakeries	7:10pm	7:30pm	11
Phone centers	10:35pm	11:06pm	24
Drugstores	7:45pm	7:45pm	26
Restaurants	11:46pm	11:55pm	33
Supermarkets	8:00pm	10:10pm	348
Tobacco	8:35pm	10:40pm	59
Taxi	10:50pm	11:50pm	14
Phone shops	9:45pm	10:15pm	15
Postal office	4:05pm	7:10pm	23
Video rentals	11:18pm	11:58pm	61

Table 12: Zero-sum Game

<table>
<tr><td colspan="2" rowspan="2">Expected clearance rate C: 9%</td><td colspan="2">ROBBER: max 1-C</td><td rowspan="2">Mixed strat. Eq.:</td></tr>
<tr><td>CLOSE to HQ</td><td>FAR from HQ</td></tr>
<tr><td rowspan="2">POLICE: max C</td><td>CLOSE to HQ</td><td>(20% , 80%)</td><td>(5% , 95%)</td><td>1/4</td></tr>
<tr><td>FAR from HQ</td><td>(5% , 95%)</td><td>(10% , 90%)</td><td>3/4</td></tr>
<tr><td colspan="2">Mixed strat. Eq.:</td><td>1/4</td><td>3/4</td><td></td></tr>
</table>

Notes: The Police can choose to keep the overlapping shift change for the neighborhood that is either far from or close to the headquarters (HQ). The robber has to victimize a commercial business that is located either close to or far from the headquarters. The payoffs are the clearance rate (C) for the police and one minus the clearance rate for the robbers. The clearance rates resemble the estimated ones (see Table 1 and 5).

Table 13: Choice of Sine and Cosine Terms

sin/cos terms	δ	se	log-likelihood	df	CV MSE	AIC	BIC
1	-0.052	0.019***	-762.825	6	11.899%	1537.649	1571.736
2	-0.049	0.019***	-759.917	8	11.891%	1535.834	1581.283
3	-0.040	0.019**	-758.308	10	11.897%	1536.617	1593.428
4	-0.034	0.022	-758.074	12	11.919%	1540.148	1608.321
5	-0.036	0.023	-757.456	14	11.937%	1542.913	1622.448
6	-0.048	0.023**	-753.273	16	11.914%	1538.545	1629.443
7	-0.035	0.024	-751.095	18	11.915%	1538.189	1640.449
8	-0.029	0.025	-750.634	20	11.935%	1541.268	1654.891
9	-0.029	0.025	-750.615	22	11.960%	1545.229	1670.213

Notes: Each line represents a different regression. δ measures the shift change effect, and "se" is the corresponding standard error. Linear probability model of clearing the case with clustered (by series) standard errors: *** p<0.01, ** p<0.05, * p<0.1. "df" measures the degree of freedom, CV MSE the mean squared error in a "leave one out" cross-validation, and AIC the Akaike Information Criteria.

Table 14: Shift Change Effects Among Shift Change Entrants

	(1)	(2)	(3)	(4)
	Cleared Robbery (0/1)			
	Fourier		'$\pm 1h15m$'	
30 minute shift change 0/1	-0.085***		-0.094**	
	(0.032)		(0.036)	
Individual shift change $\kappa = 12/10$		-0.100***		-0.113***
		(0.028)		(0.033)
Constant	0.157***	0.142***	0.160***	0.158***
	(0.028)	(0.024)	(0.029)	(0.028)
Observations	588	603	323	331
R-squared	0.028	0.029	0.017	0.024

Notes: The sample is restricted to robbers with some experience (at least one robbery) who never before organized a robbery during a turnover period. Turnover periods are defined using the 30 minute intervals (Columns 1 and 3) or using the individual measure with $\kappa = 12/10$ used in Table 6. The identification of the shift change effect is based on robbers who for the first time fall into a shift change period. Fourier regressions control for 2 sine and 2 cosine functions of time, while the $\pm 1h15m$ regressions use only robberies that happen within 1 hour and 15 minutes from the shift changes (in line with the event study dummies). *** p<0.01, ** p<0.05, * p<0.1.