# Police and Clearance Rates: Evidence from Recurrent Redeployments Within a City*

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**Abstract**

More policing reduces crime, but little is know about the mechanism. Does policing deter crime by reducing its attractiveness, or is the reduction driven by increased arrest rates that incapacitate recurrent criminals?

This paper exploits micro-level data on single robberies together with redeployments of two police forces within a city, providing first evidence of a direct link between police presenze and the likelihood of clearing cases. During shift turnovers, reduced patrolling lowers the likelihood of identifying and arresting robbers, including wouldbe repeat offenders, from 13.5 to 8 percent. Only a handful of criminals seem to systematically target these periods to exploit these inefficiencies.

Keywords: police, crime, incapacitation, clearance rates, arrest rates, deployment
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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 the crime by the mere presence of more policemen, or, more generally, by the perception that the certainty of punishment increases when there is more police on the streets (see the seminal contributions of Becker, 1968, Ehrlich, 1973). On the other hand, the additional police might solve more crimes, which would lead to more arrests, incapacitating the arrested criminals from committing additional crimes.

Uncovering whether the reductions in crime are driven by deterrence and/or by incapacitation has important policy implications. 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). Moreover, deterrence is more likely to be short lived and more likely to generate geographical or temporal spillovers than does incapacitation (see Buonanno and Mastrobuoni, 2011, for a discussion on the optimal geographic decentralization of police enforcement).[3]

This paper exploits the contemporaneous exclusive deployment of two very similar police forces together with a bizarre rotating mechanism to estimate the effect of police on clearance rates. 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. Then, in an attempt to rationalize resources, cities were divided into three parts, assigning exclusive control to the police and to the gendarmerie of 2/3 and 1/3 of the city. The assignment of these areas rotates during shift turnovers four times a day, inducing poorly coordinated and time-consuming movements of patrols across the city.

When shifts are changing, patrolling police cars need to drive from the area they were securing to the police headquarters, which are located in the city center. Once they reach the headquarters, which, based on Google map, are on average located about 15 minutes

[1]See, among others, Buonanno and Mastrobuoni (2011), Corman and Mocan (2000), Di Tella and Schargrodsky (2004), Draca et al. (2011), Evans and Owens (2007), Klick and Tabarrok (2005), Levitt (1997), Machin and Marie (2011).

[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]Incapacitation of active criminals might induce new entry of criminals Freeman (1999).

from businesses that have been victimized, a new police crew takes over and then drives the police car towards a new area of the city.[4]

I exploit the switching of these areas of deployment, as well as the exact time of robberies and the distance between robbed businesses and the police headquarters, to estimate the effect of a reduction in police patrolling on the clearance rate, defined as the probability to solve a robbery case and arrest at least one perpetrator.[5]

I show that the estimated effect represents an important mediating mechanism of the effect of police on crime (see Ludwig et al., 2011, for a discussion on mediating mechanisms). In particular, a positive relationship between clearance rates and policing is necessary to generate an incapacitation effect among repeat offenders, and, in the absence of a deterrent effect, the elasticity of crime with respect to the police equals minus the elasticity of clearance rate with respect to the police. In other words, this paper tests the mediating causal mechanism that underlies the incapacitation effect. Under some fairly innocent assumptions one can combine such relationship with the estimated elasticity of crime with respect to police to separate incapacitation from deterrence.[6]

Researchers have mostly focussed on trying to estimate the deterrent effect of police on crime, and most times using aggregate crime regressions (Durlauf et al., 2010). The next section shows that not only does one need some strong assumptions to move from an individual behavioral model of crime to such aggregate regressions (see Durlauf et al., 2010, for an excellent discussion on this), but that such aggregation is even more problematic when criminals are modelled to be potentially recurrent criminals. When aggregating over recurrent criminals clearance rates not only generate deterrent effects but also incapacitation effects. While the evidence based on aggregate data is consistent with important incapacitation effects in section 2 I explain why individual level data are needed to uncover such relationships.

Recently, researchers have used more disaggregated data over time and space to un-

[4]Section 3 focuses on the temporal and spatial distribution of robberies by the intervening police force, confirming that such reassignments do take place.

[5]According to the Milan police 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.

[6]About thirty years ago a few papers have looked at such 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 are shown to respond strongly to changes in the number of police officers. But without observing repeat offenders no links can be made between clearance rates and the counterfactual number of prevented crimes. In the criminology literature little evidence is found of an effect of police on clearance rates (Cordner, 1989, Skogan and Frydl, 2004), but little is done to circumvent the endogenous deployment of police.

cover 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.[7][8] Since the terror attacks induce a highly visible increase in police presence in particular locations, the observed drop in crime is likely driven by deterrence.[9]

Localized and abrupt changes in crime joined with highly visible and static police forces represent the ideal conditions to measure deterrence, but what would be the ideal experiment to measure incapacitation? Envisioning an experiment to measure incapacitation driven by an increase in police one quickly realizes how difficult it would be to design one. In Section 3 I argue that in such an experiment the treatment of an area should be changing some "active" police patrols into "placebo" police patrols, which are visible but inactive. This would hopefully avoid "non-compliance" of criminals, meaning criminals who select their targets in the least risky areas. Moreover, given that i) changes in clearance rates (and not just changes in police) might induce new deterrence, and ii) the mobility of criminals in an inherently dynamic nature of incapacitation, I argue that it would be hard to evaluate the effect of police on crime using crime rates as the dependent variable.[10] But with information on the distribution of repeat offenders one can use the estimated mediating mechanism to infer the counterfactual number of prevented crimes. I measure the presence of repeat offenders based on victims reports and footage from surveillance cameras, information that is gathered for investigative purposes and were provided to me by the the Milan Police Department.

[7]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..

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

[9]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 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 terrorism 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.

[10]Suppose a recurrent criminal operates mainly in neighborhoods T (the one with real police cars) and C (the one with placebo cars). His arrest would lead to a reduction in crime in both T and C. If different cities were treated to prevent such interactions, criminals might move to avoid the changes in clearance rates.

The rotating mechanism of the deployment of two separate police forces during shift turnovers generates an experiment that resembles the ideal one. Changes in patrolling that are driven by shift turnovers reduce clearance rates by more than 30 percent. The larger the distance from the police headquarters the more likely the patrol is not going to reach the victim on time during a shift turnover. Also, since the two police forces do not coordinate their movements, such likelihood is even larger when turnovers lead to a switch in police forces.

Clearly, the main threat to the identification is the potential visibility of such turnovers and the potential reaction by the offenders. The richness of the micro-level data allows me to perform several test for such "non-compliance," based not only on the composition of robbers during turnover periods, but also on the dynamic behavior of the robbers that a learning mechanism would be predict.

All the available evidence suggests not only that the incapacitation effect is robust to controlling for non-compliance, but that non-compliance is practically absent. There are three main reasons that might explain why robbers do not seem to take advantage of such turnover periods: i) information on turnover periods and on the rotation system is not easily available and would need to be inferred by robbers through direct or indirect experience; ii) the police cars are still visible for most of the turnover periods but are simply driving from or toward the police headquarters instead of patrolling the streets; and iii) several special police forces, whose cars are indistinguishable from the other ones, follow different shifts.[11]

Given that robbers do not exploit such turnover periods suggests that these periods generate a quasi-experiment that is close to the ideal experiment one would design to measure incapacitation.

This research complements research that uses redeployments after terrorism event: changes are only in mobile patrolling, as opposed to the stationing of police in front of

[11] The *reparti mobili* (mobile force), the *squadre mobili* (mobile teams), the cars of the neighborhood police and gendarmerie 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 police offices in Milan have an operating police 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 turnover periods several police and gendarmerie cars are potentially driving around the city but the patrol cars that, following an incident, get called by the police or gendarmerie 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.

vulnerable targets, and are thus harder to detect and less likely to generate deterrence.[12] Two additional papers try to look into the "black box." 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.[13] Levitt (1998), instead, uses aggregate crime regressions, identifying incapacitation from the response of specific crime rates (e.g. robbery rates, theft rates, etc.) to the clearance rates of other types of crimes. The underlying assumption is that deterrence for a specific crime depends only on the clearance rate for that same crime. Robberies appears to be the only crime for which in the event of an increase in clearance rates the the reduction in crime that is driven by the incapacitation effect dominates the deterrence effect (see Table 7). Also, Draca et al. (2011) find that for robberies there is little evidence of deterrence (see Panel B of Table 3).

But in the next Section I show that micro-founded aggregate crime regressions that allow for repeat offenders are hardly linear (or logarithmic) in the clearance rate.

# 2 Evidence from Aggregate Crime Data

Here I briefly show that starting from an individual model of crime where criminals can potentially repeatedly commit crimes complicates the aggregation of crime regressions. At time $t$ an individual decides to commit a crime when his/her expected utility from doing so is positive

$$(1 - \pi\left(c\left(p\right), p\right)) U\left[\hat{Y}_i\right] - \pi\left(c\left(p\right), p\right) D\left[S_i\right] - u_{it} > 0,$$

where $\pi$ is the perceived "clearance rate" (depends on the true clearance rate $c$ *and* on the level of police $p$. $U(\widehat{Y_i})$ is the utility from the expected loot, and $D(S_i)]$ the disutility from spending $S_i$ years in prison. $u_i$ is the opportunity cost from committing a cime (e.g. legal earnings), which is likely to be fairly persistent across individuals. Such persistence is going to introduce repeat criminal behavior.

[12] Skogan and Frydl (2004) review the criminology literature on the effectiveness of police. The studies that evaluate the effect of police 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.

[13] Due to coding errors the initially very precise estimates lost some significance (Hutchinson and Yates, 2007, McCormick and Tollison, 2007).

The likelihood of committing a crime is going to be

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

where $F$ is the cumulative distribution function of $u_i$. $F$ is (implicitly) assumed to be uniform when running aggregate crime regressions where $c$ enters linearly (under the additional assumptions that perceived clearance rates equal or are proportional to the real ones) Durlauf et al. (2010).

What are the expected crimes for this individual before an arrest is made? Assuming exogenous arrival of of criminal opportunities, where $T_i$ measures their total number:

$$C(c) = \sum_{t=0}^{T_i} F\left(-\pi\bullet\right)\left(1-c\right)^t.$$

If for simplicity $F\left(-\pi\bullet\right)$ is assumed to be persistent over a few months, for large $T_i$s

$$C(c) \approx \frac{F\left(-\pi\bullet\right)}{c}.$$ [14]

$1/c$ is clearly convex with respect to $c$, while for $F\left(-\pi\bullet\right)$ such relationship depends on the functional form of $\pi(c(p), p)$ and on the distribution of $u_i$. Aggregate crime regressions implicitly assume that perceived clearance rates equal the true ones and that the distribution is uniform, therefore generating a linear relationship between $C$ and $c$.[15] Figure 1 plots 20 years of yearly province level aggregate crime rates for robberies and for motor vehicle thefts against the respective 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.[16]

While the convexity is consistent with incapacitation of repeat offenders, several identification issues plague statements based on aggregate data. Overall clearance rates are

[14] The upper quartile time difference between crimes organized by the same robbers is two weeks, meaning that 75 percent of robbers would most likely organize more than 26 robberies in a year. Since clearance rates are in the order of 13 percent (Table 1), the approximation is fairly precise.

[15] Since such distribution is likely to resemble an unimodal earnings distribution, assuming that perceived clearance rates equal the true ones ($\pi = c$) the relationship between $F$ and $c$ would be decreasing and convex if the marginal criminal lies below the mode and decreasing and concave otherwise.

[16] On a related note, trying to measure incapacitation using the relationship between arrests and police would be a mistake. As Levitt and Miles (2004) and Owens (2011) point out, the theoretical predictions about arrest rates are ambiguous. More police 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.

known to be subject to measurement errors, for example, the clearance might happen the year after the crime happened.[17] Clearance rates depend on police enforcement and are thus likely to be endogenous. Moreover, even if $F$ was uniform, due to the non-linearity that is driven by the incapacitation effect, the crime regression would highly non-linear.[18]

Analyzing individual level clearance rates allows one to bypass all these caveats.

# 3 The Ideal and the Quasi-Experiment

In the ideal experiment aimed at measuring incapacitation the "treatment," meaning the increase in police, 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 varying 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 likely generate a gradual and potentially hard to identify reduction in crime rates, as well as deterrence as criminals start perceiving the increased incapacitation (assuming the effective police cars lead to additional arrests). Alternatively, to avoid interactions across treated and non-treated areas driven by the mobility of criminals (insuring what the policy evaluation literature calls the stable-unit-treatment-value), one could randomly assign treatment to large areas, or better entire cities. But again, perceptions about the increased productivity of the police 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 clearance rates (the mediating mechanism). Exploring the mediating mechanism that works for single robberies 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. To extrapolate the incapacitation effect of policing from the effect policing has on clearance rates one needs to know i) whether the arrests lead to prison time, and ii) the

[17] Clearance rates are also subject to selection, as averted crimes are not measured in $c$ Cook (1979).
[18] $\pi(c(p), p)$ could also potentially be non-linear if robbers misperceive small probabilities.

counterfactual number of crimes the arrested robbers would have attempted.

Regarding point i), clearing a robbery is almost always synonymous with at least one arrest.[19] Based on data collected by the police the 31 series that were cleared in 2008 led to a total of 203 years in jail, the 39 cleared in 2009 to 217 years in jail. 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. Of these robbers, only one was found not guilty and 4 were given alternative sanctions instead of prison.

Regarding point ii) the counterfactual number of crimes depends on the distribution of repeat offenders and their offences, as they are the ones whose arrest would generate a *future* reduction in crime. But 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 data available allow me to reconstruct the "survival table" of robbers. Table 2 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 rates 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 police perfectly observes each robber, they are likely to be lower-bounds. It is thus safe to say that higher clearance rates generate subsequent incapacitation effects.

The quasi-experiment is based on quasi-random redeployment of two police forces, the police and the gendarmerie, within the same Italian city, Milan, during shift turnovers. Italy has two separate police forces that share the same functions and objectives. The *Carabinieri* were the royal police force, the gendarmerie, and despite the 1945 referendum that ended the monarchy in favor of the republic, they were not dismantled. Up until the end of the 1990s the two police forces were operating side by side, without communicating with each other. The government decided that to save resources the two forces would be responsible for keeping law and order each in a different part of the city. The area under study, which comprises the municipality of Milan (*Comune*) as well as part of the smaller

[19] According to the police two times they waited to make the arrest of identified perpetrators only to gather additional evidence.

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.[20][21]

For police deployment purposes the city is divided into 3 areas, West, North-East, and South-East; the Western 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 South-Eastern part). At any given point in time one area is under the control of the gendarmerie, and two under the control of the police.

Most likely because of a lack of agreement about how to split the assignments such assignments rotate every about 6 hours, in concert with shift turnovers. The assignments to the three areas rotates counterclockwise. Given that there are two forces, three areas, and four 6-hour shifts within a given day, the gendarmerie covers the same area during the same 6-hour shift only every three days. This means that 7 to 10 cars that cover around 120 square kilometers (40 square miles) inside each area spend some of their time transiting through areas they do not have control over. It also means that there is quasi-random variation in the days of the month, days of the week, and 6-hour shift in the geographic coverage of police forces. Figure 2 shows the distribution of robberies in Milan based on the day triplet, where the robberies that are under the responsibility of the gendarmerie have a black square. One can see that in day/time combinations that belong to group 1 the gendarmerie covers the South-Eastern part of the city from 12am to 7 am, then the North-Eastern part from 7am to 1pm, the Western part from 1pm to 7pm, and finally again the South-Eastern part from 7pm to 12am. During days of type 2 and 3 the initial assignment differs, and so does the entire sequence.

The outliers are driven by cars that, as mentioned before, are part of the non-rotating smaller police or gendarmerie forces.[22] This paper uses shift turnovers that happen about every 6 hours as a measure of a reduction in the efficacy of police forces. Whenever a shift ends and there is a shortage of police cars, which based on informal conversation with police officers seems to happen quite often, cars enter the police stations and new crews take the place of the old ones. Every time during a turnover different shifts share

[20]One can easily compute the land area covered by robberies approximating the such area with a circle, and using the fact that the radius is between 10 and 11 km (7 miles).

[21]The crime rates and clearance rates for Milan in 1983 and 2003 (see Figure 1) show that the city does not represent an outlier.

[22]The neighborhood police forces, the mobile forces, and the motor-bikers follow also different shifts (8am-2pm and 2pm-8pm).

the same police cars there is a considerable weakening of police control over the city.

The police and the gendarmerie do not coordinate such turnovers which means that if there are delays of either the outgoing or the incoming cars for a short period of time there might either be twice as many cars compared to the planned ones or no cars at all in the neighborhood.[23] But when there are twice as many police cars only one would be responsible for maintaining law and order. This means that whenever turnovers change the police force that has control over a given area disruption is more likely. This happens for two out of three areas. Having control over two areas, for one of these areas the police retains control and disruption should be less pronounced.

Nonetheless, even for those areas at least some disruption is possible. This happens whenever there is a shortage of police cars, which according to the Police Union SIULP happens frequently. Different shifts will then share the same cars, and such cars need to drive in and out of the police headquarters.[24] 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.

Unfortunately there are no data on response times of the police, or data recording the exact location of police cars over time–such data would require immense storage capabilities–which means that there is no direct measure of the average reduction of police during turnovers.[25] Given that the average distance between incident locations and police headquarters is close to 15 minutes in most analyses I take 30 minute intervals around turnovers to measure the reduction in police (15 minutes to drive in and 15 minutes to drive out of the headquarters). Later in Section 4.4 I show that the analysis which uses Google's estimated time to drive from the police headquarters to the location of the robbery produces quite similar results.

Sometimes there are enough police cars to operate the turnover while patrolling, and so the estimates can be viewed as intention to treat effects, or upper bounds of the true reduction in clearance rates. Parameterizing how the likelihood of treatment depends on the distance in time between the exact time of the turnover and the time of the incident and on the distance in space between the incident location and the police headquarters

[23] The two forces are by all means two separate entities. They also have separate emergency telephone number (112 and 113), and the operator would forward the call to the other police force depending on who is covering the area at the time of the crime.

[24] According to the Police Union SIULP in Milan there are on average between 15 and 20 police cars patrolling the streets, but on average only 25 cars that are fully working (Biondini, 2011, Office, 2011). This means that typically there are not enough cars to operate all turnovers while patrolling the streets. I could not find this information for the gendarmerie.

[25] Thaler (1977) finds little evidence that response time matters, though this might depend on response time being endogenous.

one can try to recover the average treatment effect (see Section 5).

The main difference between the ideal experiment and the actual one is that treatment is potentially predictable. If criminals knew about such rules they could try to reconstruct the rotation mechanism and target the least patrolled areas.

But it seems that turnovers are almost completely undetected and unexploited by the offenders: i) overall, robbers do not seem to target businesses during turnovers, and they don't seem to target during turnovers those businesses that are farther away from the headquarters or those businesses where control of the area is switching from one police force to the other; ii) the characteristics of the robberies do not change during turnovers; iii) more able robbers, defined as those who are more unpredictable and, therefore, more successful, are not more likely to target businesses during such periods; iv) controlling for the experience of robbers, measured by the number of successful robberies, does not alter the incapacitation effect.

These tests are increasingly sophisticated and are more and more able to measure whether at least a minority of robbers is aware of the disruptive power of turnovers, but rest on the assumption that learning about the treatment effect evolves smoothly over time. If, instead, learning happens in discontinuous manner and depends little on experience, previous tests might be unable to have enough power. The v) test shows that robbers who happened to commit a robbery during a turnover (and thus might have learned about the treatment) are not more likely to do so again in their subsequent robbery. The vi) test shows that the turnover effects based on robbers who for the first time happen to perform a robbery during a turnover and therefore are less likely to have deliberately chosen such periods are if anything even more pronounced.

# 4 Milan Police Data

## 4.1 Data

The data on robberies are collected by the police of Milan for investigative purposes. After each robbery the police collects all kinds of information about the perpetrators, the victim, the loot, etc.[26][27]

The police not only surveys the victims, but also collect any available information that is recorded by surveillance cameras. Their main purpose is to identify recurrent perpetrators in order to predict future robberies. Such methods are called *predictive policing*. I have been given access to a subset of these data, and the summary statistics are shown in Table 1.

Each observation is a separate robbery. Over the period 2008-2011 there were around 2000 separate robberies in Milan. According to the Milan police 70 percent of these robberies show some link with other robberies, meaning that at least one robber was involved in at least two of them. The police uses information taken from surveillance cameras together with very detailed descriptions by the victims about the robbers to link offenders across robberies. 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, and the series with the largest number of robberies has 49 of them. Such number is later used as a proxy for experience. The Table shows that 12.7 percent of robberies are cleared when each robbery is treated as an independent observation, while in terms of series of robberies, 53 percent of them are cleared by June 30, 2011, which is when the data collection ends.

The Police variable indicates whether the police handled that particular robbery. While the city is divided into 3 parts and the police is responsible for 2 parts, the fraction of robberies that is handled by the police is slightly larger than expected (73 against 67 percent). Turnover 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 beginning of the 7am-1pm shift. Those four half-hour periods cover almost 16 percent of the data. The "persistent" shift variable is equal to one whenever the police covered the area where the robbery happened during the previous shift. Given that there are 2 areas out of three that are covered by the police it is not surprising that the fraction of such areas is equal to 30 percent.

[26] Data are missing for weapons, nationality, and age 7, 8 and 10 percent of the times, respectively. To increase the sample size I have imputed the missing values using simple linear regressions of the missing variables on the loot, the number of offenders, and the type of business that was targeted. R-squared are between 6 and 10 percent. Given the random nature of the experiment excluding those observations the results are basically unchanged.

[27] The police 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).

## 4.2 Distribution of Robberies

Regarding evidence on robbers targeting turnover periods, Figure 4 plots the distribution of robberies in 15 minute intervals. Most robberies happen around late morning or late afternoon. The peak is just before most businesses are about to close (time goes from 0 to 24), and when darkness aids the escape.[28] The spike in robberies is not during the 7pm turnover, but between 7.15 and 7.30, which we will see is too late to exploit the reduced clearance rates.

I was also able to collect data on the distribution of thefts in the city of Milan for every 15 minutes between 2008 and 2009. The daily number of thefts are shown in Figure 5. While there are on average only 1.5 robbery each day there are about 3 thefts every 15 minutes. None of the average number of thefts shows a clear spike during turnovers. Bag-snatches and pick-pocketing are high during the entire day. Burglaries spike in the morning when victims are likely to realize the theft, while other thefts spike around 8pm.

The next sections are going to formally test the differences in the number of robberies.

## 4.3 Identification Strategy

The simplest way to estimate the effect of a turnover on the clearance rate is to compute a simple difference. Table 3 shows that clearance rates are equal to 8 percent during turnover periods and equal to 13.7 percent otherwise. Such simple difference is significant at the 1 percent level. Panel B of the same table shows that the difference is driven by the turnovers that happen during the day, especially at 1 pm and at 7 pm (92 percent of robberies that happen during a turnover period happen either at 1 pm, 22 percent, or at 7pm, 70 percent). With the exception of the 18 robberies that happen during the midnight turnovers, clearance rates are between 5 and 7 percent lower during turnovers than during the rest of the day.

Controlling for all 30 minute time intervals which contain at least 2 percent of the robberies, which excludes mainly night times, the results are very similar (Table 4). The first column uses only robberies that happen during the day, while the second columns uses the whole sample. The excluded 30 minute periods, for which less than 40 observations are available to provide an estimate, display a dash. During these periods clearance rates are close to 15 percent, and drop to about 9 percent around 1pm and around 7pm, though the effect is only at the margin of being significant at midday.

[28] In Section 4.3.4 I will show that there is enough variability in closing time to test whether closing time are driving the changes in clearance rates.

The next step is to test whether the 6 percentage points reduction (-40 percent) in clearance rates is driven by either an underlying evolution in clearance rates over the day that happens to coincide with turnover periods, or by an underlying selection mechanism. If offenders, in particular the more able ones, were systematically targeting such periods, such a selection might be driving the observed reduction in clearance rates.

Like in a regression discontinuity design (with several discontinuities), there are two ways to control for the underlying evolution of clearance rates: i) comparing turnover periods to nearby periods (Section 4.3.1), and ii) controlling the evolution for a flexible function of the time of the day (Section 4.3.2).

There are several ways to test for selection. The first is to look at the mere distribution of robberies during the day. One would expect to see several robberies, or other crimes, during shift turnovers if criminals were expecting those periods to be the best ones to perform a robbery. This test is in spirit very similar to testing whether there is "manipulation of the running variable in the regression discontinuity design" (McCrary, 2008). The second is to test whether robberies that take place around turnovers are different than the other ones. This test resembles the regression discontinuity test in other covariates. If other covariates are found to be discontinuous around turnovers the "justification of the identification strategy may be questionable" (Imbens and Lemieux, 2008). In Section 4.3.3 I define several placebo turnover periods to test for jumps at non-discontinuity points (Imbens and Lemieux, 2008, see again). Such tests allow me to see whether the estimated turnover effects are unusual in terms of both their size and their significance level.

All the selection tests I just mentioned use very detailed information on the timing of the robbery but no information about the evolution of the robberies. Exploiting the panel structure of the data additional tests for selection, shown in Section 4.3.5, go beyond simply testing discontinuities. These additional tests are designed to look for evidence of learning, testing whether at least *some* robbers systematically or at least after some time target business during turnover periods.

While one doesn't observe a clear spike in robberies during turnovers, it might still be that more able robbers (even if small in numbers) are systematically targeting shift turnovers. The most intuitive way to test whether there is such a selection is to perform randomization tests (the second selection test mentioned above). In Mastrobuoni (2011) I show that more able bank robbers tend to work in groups and use firearms. They also tend to rob higher amounts. If this finding generalized to all robbers one would expect that during turnovers robberies with these signals of ability would be over-represented.

If shift turnovers lead to reduced patrolling but robbers are unaware of such short changes in police presence one would expect the number as well as the average characteristics of the robberies (the observables and the unobservables) to be similar just before and just after such periods, with one exception: clearance rates.

### 4.3.1 Differences With Respect to Nearby Periods

I take 30 minute periods around the time of turnover $T$ compared to periods $m$ minutes before and after the turnover for different outcomes $Y$. The choice is driven by the fact that according to Google Maps 15 minutes is about the median and mean time it takes to drive between the incidents' locations and the headquarters (see Table 1). Given that traffic increases this estimate and that around half of the time cars need to drive from the incidents' location to the police headquarters *and* back a total interval of 30 minutes seems to be a reasonable choice, but later in Section 4.4 I will see whether the results are robust to changes in the time interval. In particular, I will try to estimate the intention to treat (ITT) effect taking Google's estimated time into account. For now, the ITT turnover effect is simply:

$$\delta = E(Y||t-T| \leq 15) - E(Y|15 < |t-T| \leq m)),$$

and can be estimated on robbery $n$ perpetrated by the group of offenders $i$ using the following regression function

$$Y_{i,n} = \alpha + \delta I(|t_{i,n} - T| \leq 15) + \epsilon_{i,n}, \tag{1}$$

s.t. $|t_{i,n} - T| \leq m$.[29]

The first column in Table 5 presents the estimated $\delta$s using robberies that happen between 5pm and 9pm, thus 2 hours before and after the 7pm turnover, where around 50 percent of all robberies take place. In all the regressions, for all the samples the only one outcome has a $\delta$ that is significant at the 5 percent level, the clearance rate. Little changes when in column 4 I extend the analysis to all shift turnovers, taking 2 hour intervals around each shift. Notice that the coefficients on the variables that are assumed to signal ability show no significant changes, and the one on loot and on firearm use often have the opposite sign compared to the one expected under selection. The next column uses the whole sample controlling for a smooth function of time.

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

### 4.3.2 Fourier Sine and Cosine series

Instead of focussing the analysis on just the periods before and after turnovers one can alternatively use the whole sample. 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 functions.[30] Since time repeats itself in cycles such approximations are even more valuable. Andrews (1991) shows that under some smoothness conditions a truncated Fourier series estimated using least squares converges to the true periodic function.[31]

The smoothness assumptions are similar to the ones used in regression discontinuity designs when modeling the running variable using a continuous function. The regression model to estimate the effect of turnovers controlling for time is:

$$Y_{i,n} = \alpha + \delta \sum_{j=1}^{4} I(|t_{i,n} - T_j| \leq 15) + \sum_{j=1}^{k} (\gamma_j \cos(j \times 2\pi H_{i,n}) + \delta_j \sin(j \times 2\pi H_{i,n})) + \epsilon_{i,n}, \quad (2)$$

where $T_j, j = 1, 2, 3, 4$ indicate the time of the turnovers, and $H_{i,n}$ indicates the time of day standardized to lie between 0 (midnight) and 1 (midnight $+\epsilon$). The Fourier Sine and Cosine series allows one, due to its $2\pi$ periodicity, to estimate a flexible function of time with the additional constraint that in the limit at midnight and midnight minus some small amount of time the predicted values are the same. Given that most businesses are only open during the day, one needs to choose where to truncate the series, or how to set $k$. This choice serves a similar role here to the bandwidth parameter for non-parametric kernel estimations. Before explaining how to do this, let me anticipate that the optimal $k$ is equal to 3.

The last column of Table 5 shows the results using 3 sine and 3 cosine terms. The estimated $\delta$ is equal -4.1 percent and is not very different from the one obtained based on time intervals. Apart from larger standard errors for the haul variable that is driven by some outliers that enter the sample, column (5) is quite similar to column (4), and again the only significant coefficient is the one on turnovers. Overall, the regression estimates in Table 5 are consistent with large reductions in clearance rates that are not driven by selection.

[30] 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."

[31] He also proves the asymptotic normality of such estimators.

Figure 8 shows how the polynomials of sine and cosine terms approximate the evolution of clearance rates over the entire day. Predicted clearance rates tend to be lower during shift turnovers than during nearby periods, both locally and globally. Even when estimating a different change for each turnover the picture is still the same (though with larger confidence intervals for the changes). Clearance rates are on average 4.1 percentage points lower during turnovers, which corresponds almost to a 30 percent reduction.

Going back to the 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.[32] Table 6 shows that using this simple but slow "leave-one-out" cross-validation method, $k = 3$ minimizes the cross-validation mean squared as well as the AIC objective function. But $\delta$ is large and significant all the way up to 7 sine and 7 cosine terms.

#### 4.3.3 Placebo Test

In order to rule out that chance and variability in clearance rates are driving the results one can run placebo tests. The idea is to sequentially take different 30 minute intervals within a 4 hour window and treat them as if they were turnover periods. To preserve some power I select 30 minute intervals where at least 3 percent of the robberies take place. There are 28 such 30 minute periods between 11.15am and 8.15pm. Therefore, one can start with the placebo turnover around 11.15am, estimate a $\delta$ using a 3 hour interval around that time and than move to 11.30am, etc. Figure 7 plots the different $\delta$s from the lowest to the largest, together with the corresponding 95 percent confidence interval. The two lowest 30 minute intervals are 1.15pm (shown in the figure in decimal fractions of 24 hours, 13.25) and 7pm (19) are turnover periods or close to turnover periods, and so is the forth one 12.45pm (12.75). But only the 7pm effect is also significantly different from zero. The 11.45am (11.75) are instead positive and significant though part of the effect is likely to be in part driven by the 1pm turnover periods being in the control group. All the other periods are in absolute terms smaller in magnitude and never even close to being significant. Overall, the placebo test shows that the real turnover periods happen to be the ones with the most negative effects on clearance rates, and the most significant ones as well. The likelihood that both events happen just by chance should be fairly close to zero.

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

In order to formally test whether robbers target turnover periods one can run a similar placebo test based on the *number of robberies* that fall in a given 30 minute real or "placebo" turnover period. In order to run such placebo tests on the number of robberies one needs to aggregate the data over time (I chose 15 minute periods). The left panel of Figure 7 shows that several placebo turnover periods appear to have a large number of robberies compared to 1 and 1/4 hours before and after such periods, including the 7pm one, but such difference is only significantly different from zero for the 7.15pm and the 7.30pm placebo periods. Next I analyze whether turnovers are more disruptive when the police forces move into a freshly patrolled area, or more disruptive the longer the distance between the location of the robbery and the police headquarters. And if they are, an additional test for selection is to see whether more disrupted turnovers turn out to be the most targeted ones.

#### 4.3.4 Other Regressors and Heterogeneity of the Effect

Consistent with the evidence about the orthogonality of the turnover periods with respect to the characteristics of the robbery (with the exception of clearance rates), column 1 of Table 7 shows that results do not change when adding a number of controls, namely day of the week, police, area, foreigner, year, and closing time dummies, as well as a cubic in age, the number of robbers involved, and the experience of the robbers ("Number of the series"). There are two proxies for the shops' closing times. These are computed diving business into 23 homogenous categories and taking the maximum and the 90th percentile of the time of the robberies.[33]

This means that even controlling, among other things, for the experience of the robbers (which does decrease the likelihood of being arrested) the effects are still there. The police appears to be more efficient than the gendarmerie (despite the apparently random assignment of cases). This is not surprising given that the police set up the whole data gathering, and developed the predictive policing software. And the South-Eastern area of the city has higher clearance rates. The other variables do not influence clearance rates, including the closing times.

Next I compute the turnover effect depending on the distance from the headquarters as well as on the switching of responsibilities across police forces. Given that the police and the gendarmerie do not coordinate the turnovers in real time, turnovers should be more likely to be disruptive when the responsibility over an area switches from one force to the other. Defining such turnovers as "non-smooth" column 3 shows that only non-smooth

[33]See Table 14 in the appendix.

turnovers lead to a significant reduction in clearance rates (-4.4 percent). Smooth ones lead to a smaller reduction, -2.1 percent, but the difference is not significantly different from zero.

Given that police and gendarmerie cars start their turns from their headquarters one can test whether turnover effects depend on the distance between the headquarter and the location of the incidence. Locations that are farther away from the headquarters should be more likely to suffer from some lack of patrolling. The last column of Table 7 separates the effect of turnovers depending on whether the distance in minutes from the police headquarters, computed using Google Maps, is above or below the median.[34] While only the robberies that happened far from the police headquarters during a turnover show a significant reduction in clearance rates (-5.4 percent) even those that are closer show a negative reduction (-1.8 percent). Again, there is not enough power for the difference to be significant. Later in Section 4.4 I will use Google's information on the time it takes to travel from the headquarters to the incident's location together with the time of the incident to define whether the police car was or wasn't likely to be present when the robbery happened.

Like before, one would expect that robbers would try to exploit these differences in clearance rates. To test whether robbers are more likely during turnover periods to target businesses that are farther away from the headquarters or businesses that are in an area that is subject to a non-smooth turnover one needs to aggregate the turnovers by time. Table 8 presents linear models of the number of robberies falling in a given 15 minute period averaged over the variables needed to define whether a turnover is smooth or not (3 groups of days and 3 areas) and the variable defining whether the distance is above or below median. No matter how one chooses the sample and the method to test for a discontinuity in the number of robberies, there is no evidence that robbers target non-smooth turnovers. If anything there seems to be a slight preponderance for smooth ones. There is also no evidence (columns 5-8) that during turnovers robbers are more likely to target locations whose distance from the headquarters is above the median (only for the 12pm-2pm period the coefficient on the above median dummy interacted with turnover is larger than the corresponding one for the below median distances).[35]

The next test of selection make use of the longitudinal aspect of the data.

[34]Using the distance in kilometers the results are very similar.

[35]Notice that the significance of the turnover coefficients in in columns 3, 4, 7, and 8 is driven by the evening peak in robberies, but as already shown in Figure 7 the real peak seems to be after 7.15pm.

### 4.3.5 Longitudinal tests for non-compliance

The previous section has shown that i) robbers do not seem to, in general, target turnover periods, and, in particular, target those that are more likely to lead to disruptions; ii) that clearance rates change during turnover periods while the average characteristics of the robberies don't. But related to i) we don't know what the counterfactual distribution of robberies would have been without turnovers (the test rests on a smoothness assumption), and related to ii) the other regressors might not capture ability well enough.

Fortunately the longitudinal aspect of the data can be exploited to design more powerful tests. In particular, one can i) exploit the longitudinal aspect of the data to measure ability, and ii) test for the presence of learning by analyzing the evolution of the likelihood to perform a robbery during turnovers.

Related to i), one should expect more able robbers to be more likely to target businesses during turnover periods, and related to ii) robbers who learn about any disturbance to the patrolling due to shift turnovers should become more and more likely to target such periods.

One can exploit the longitudinal aspect of the data to measure the ability of robbers. 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 9. The Figure plots, for each 244 group of robbers who performed at least 2 robberies, the total number of performed robberies against the average distance between subsequent robberies one. 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 0.55 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.[36]. Regressing the total number of robberies on the fraction of robberies that were done during turnover periods one again gets a coefficient which is positive and significant. A standard deviation increase (0.20) in the fraction of robberies performed during turnover periods has almost the same effect as a standard deviation

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

increase in the average distance. If choosing a turnover 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 9 shows that this is not the case. The regression line is flat and if anything has a negative slope.[37]

As for the evidence on learning, Table 9 shows the distribution of the total number of robberies performed. The first row indicates that 663 robbers or group of robbers either end their actions with an arrest (last column, 21 percent) or simply do not perform other robberies. For 68 robbers or group of robbers there are two robberies (43 percent of them end up getting arrested), etc. The last column indicates that the robber or group of robbers with the highest number of performed robberies did 49 before getting arrested. The one but last column indicates the fraction of robberies that are done during turnover periods (1/2 hour intervals). The overall average is 16 percent, and up to a total of 18 robberies the likelihood of falling in a turnover period is not very different from 16 percent. As for Figure 9 offenders with more robberies appear to disproportionately select turnover periods. But it would be misleading to interpret such a correlation causally. After all if clearance rates are lower during turnover periods such a correlation might emerge even without selection.

The easiest way to see this is to observe the evolution of the time chosen by the individual offenders across robberies. The 8 panels of Figure 10 show the evolution of the time chosen by the 8 most prolific robbers.[38] These offenders happen to disproportionately organize a robbery during shift turnovers but no clear learning pattern, like a convergence toward turnover periods, seems to arise.

The one but last group of offenders is the only one where the time chosen seems to converge toward turnover periods. For all the other ones either no pattern arises or the series ends when the offenders start targeting times when the police is fully operational. This seems to be the pattern for the first, the second, and the forth group of robbers. They seem to start by targeting turnover periods, with some outliers, and when they end up outside such periods they get arrested. This seems to be the overall pattern for the whole sample. The correlation between the turnover dummy and the number of the series is equal to 0.003 with a standard error of 0.001, but conditional on either individual fixed effects or on the maximum number of the series the correlation becomes negative (-0.006 with a standard error of 0.002). This means that conditional on ability (or luck), robbers

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

[38]The 8 groups of robbers represent 236 (11 percent) of all robberies.

are not more likely to target turnover periods as they get more experienced.[39]

The simplest way to directly test whether the results are driven by selection is to compute the turnover effect on just the sample of offenders who have never before organized a robbery during a turnover. If these are the ones who are more likely to end up just by change and not because of their ability inside a turnover period, focussing on these robbers one would expect to find a smaller turnover effect on clearance rates. In Table 10 I compute the turnover effect $\delta$ using three different methods: a simple difference, a difference controlling for sines and cosines, and the difference using two hours intervals around turnovers. Rows (1), (3), and (5) condition the sample on offenders who up until their previous robbery (this method excludes the first robberies) have never performed the robbery during a turnover period. The coefficients measure the difference in clearance rates between offenders who for their first-time organize a robbery during a turnover period and those who have never organized a robbery during a turnover period. For completeness rows (2), (4), and (6) show the difference for the sample complement, those who have already robbed a business during a turnover period. There are no appreciable differences between the estimates based on the two samples, and if anything first-timers have slightly larger reductions in clearance rates. This indicates that, as long as the learning is not sudden and discontinuous, selection cannot explain the differences in clearance rates.

But even if learning was discontinuous one would expect at least some sort of convergence toward turnover periods. While Figure 10 seemed to show that this wasn't the case for almost all major offenders, one can test whether convergence comes about for the entire sample. The simplest way to test this is by estimating whether the probability of organizing a robbery during a turnover depends on having organized the previous robbery during a turnover. Table 11 shows the coefficients of the following linear probability model: $\Gamma_{\tau,n} = \sum_{\tau=1}^{4} \rho_{\tau,n-1}\Gamma_{\tau,n-1} + \epsilon_{\tau,n}$, where $\Gamma_{\tau,n} = I(|t_n - T_\tau| \leq 15)$ is the shift turnover dummy for the n-th robbery at the beginning of shift $\tau$. The number of the individual robbery is indexed by $n$ and the offender subscript is not shown for simplicity. There are too few robberies to estimate this model for the morning ($\tau = 1$) and night ($\tau = 4$) turnover period. For both turnover periods there is some persistence, meaning that the turnover dummy $\Gamma_{\tau,n-1}$ of robbery $n - 1$ predicts the turnover dummy of the n-th robbery (Table 11). There is no evidence instead that, compared to offenders whose previous period was not a turnover period, offenders who were in a turnover period that is different from $\tau$ jump to turnover $\tau$. While there is no evidence that robbers move across turnover periods there is some evidence of persistence within the same turnover

[39]For brevity the coefficients are shown only on Table 15 of the online appendix.

periods, especially at 1pm. That persistence drives the overall persistence of falling into any turnover period (column 3). But the last two columns shows that the persistence is common to many other time periods.

Defining a placebo turnover period anticipating or postponing the actual shift turnover by 30 minutes results in equally high persistence. Instead of choosing those two placebo turnovers one can estimate the persistence for several 30 minute periods and than see whether the estimate of persistence one gets around 7pm and 1pm is significantly different from the other ones. Figure 11 shows the density and the cumulative distribution function of the 31 different estimates of persistence ($\rho$) one gets using different 30 minute periods between 8.15am and 11.15pm (during the night there are too few robberies to estimate $\rho$). In other words, I estimate autoregressive models $h_n = \rho h_{n-1} + e_n$ over the entire sample, where, for example, in the first regression I model the probability to organizing a robbery between 8.15am and 8.45am as a function of having organized the previous robbery during the same period.

The vertical dashed lines show the estimated persistence at 1pm and 7pm. While the 7pm $\rho$ coefficient is in the middle of the distribution the 1pm is not. This does suggest that for the few offenders who rob businesses around the 1pm turnover (67 robberies, or 3.1 percent of the total) some learning might be in place. But the level of persistence is around 20 percent and is far from 1. Given the small number of offenders who rob businesses at 1pm excluding the few robberies that happen around 1pm changes the estimated $\delta$s only marginally, and the changes are even more pronounced (the results are shown in the appendix Table 16).

## 4.4 Robustness Checks

In Equation 1 $\delta$ has been defined with a cut-off value of 15 minutes. But one can exploit information on the exact location of the incident, and Google's predicted duration $\tau$ of driving from the gendarmerie or the police 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.

$$Y_{i,n} = \alpha + \delta I(|t_{i,n} - T| \leq \kappa \tau_{i,n}) + \epsilon_{i,n}. \tag{3}$$

Table 12 presents the estimated $\delta$s using $\kappa$ from 1 to 1.5 in increments of 1/10. Overall the results are quite similar to the one based on 30 minute intervals. Slightly larger estimates are obtained using $\kappa = 1.3$. Given that Google's estimated travel time do not take traffic into account and that police cars have the option to turn on the siren a 30 percent increase in travel time seem to be a reasonable estimate.

The last robustness check is going to make sure that the results are not biased due to spillovers across robberies. If a cleared robbery is more likely to distract the police than one that is not immediately cleared the timing of one robbery might influence the subsequent ones. Table 13 computes the turnover effects focussing on either just the first robbery of a day that a given police force has to deal with (Columns 1 and 3), or, even more conservatively, on just those days where police forces deal with just one robbery (Columns 2 and 4). The evidence shows that the results are not biased due to spillovers.

# 5 Conclusions

Using precise micro-level information about robberies against businesses coupled with some peculiar shift-turnover rules, this paper is, to the best of my knowledge, the first one to show that reducing and disrupting police patrolling without influencing its deterrence potential reduces the likelihood of clearing a robbery and arresting at least one of the perpetrators. A battery of highly diverse selection tests shows that, with maybe the exception of robbers who target the 1pm turnover period, robbers do not exploit such turnover periods.

The reason why there doesn't seem to be any major (negative) deterrence is likely to be lack of information about shift turnovers. 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 already discussed, some minor police squads, whose cars are indistinguishable from those which rotate, do not rotate, and follow different shifts.

The data do not allow one to precisely measure the reduction in policing during turnovers, but according to the Police Union the average number of working cars is 25, while cars on patrol range between 15 and 20.[40] This means that between 1/3 to 2/3 of patrolling cars need to perform the shift turnover inside the headquarters. This also means that for the remaining 2/3 to 1/3 of cars the shift turnover is potentially less disrupting.[41] In order to compute average treatment effects one has to divide the ITT by such fractions. Taking the estimated -5 percent ITT, 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

[40] Unfortunately only the average number of working cars and not its whole distribution is know.

[41] No equivalent statistics are available for the Gendarmerie.

likelihood of immediately clearing a robbery is close to zero, which is consistent with the fact that most arrested robbers are caught in flagrante.[42]

One can use the ATE together with an estimate of th elasticity of robberies with respect to police to evaluate the relative strength of incapacitation and deterrence. Using the elasticity estimate from Buonanno and Mastrobuoni (2011) $\frac{\partial C}{\partial p}\frac{p}{C} = -1.1$, and assuming there is only an incapacitation effect:

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

Since $\frac{ATE}{c}$ is equal to $\frac{0.05/0.5}{0.15}$ (I took the midpoint between a reduction of 1/3 and 2/3), the implied incapacitation elasticity is 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.

Finally, in terms of policy implications the quasi-experiment highlights that having two police forces within the same city that do not cooperate is clearly inefficient. Turnovers where a police force maintains control over the same area appear to be half as disruptive as the ones where control passes from one force to the other. On top of that, information about the robberies is less likely to be shared across the two police forces than within one of them.

Apart from the potential lack of coordination and potential loss of information about the criminals, this paper also highlights the issues related to shift turnovers. If robberies were the only crime a clear policy implications coming from this study would be to organize shift turnovers when most businesses are closed and robberies are rare. The fraction of robberies that fall within a 30 minute turnover period can be drastically reduced from 16 to 2.3 percent by deferring all turnovers by just one and a half hours (1.30am, 8.30am, 14.30pm, 8.30pm). One can estimate the change in the expected number of robberies given by such a minor change, a change that is unlikely to upset the logistics of the police.

Such change is equal to $\sum_{\tau=1}^{\infty} p_{t,1}^{\tau} - \sum_{\tau=1}^{\infty} p_{t,0}^{\tau}$, where $p_{t,i} = 0.865 + 0.055 I(|t - T_i| \leq 15)$ represents the probability of success of a robbery, which depends on whether the robbery happened during a turnover period.[43] Postponing the turnovers by 1.5 hours lowers the probability $P(|t - T_i| \leq 15)$ from 16 percent to 2.3 percent. For recurrent criminals the

[42]Unfortunately the police does not record for all robberies whether an arrest happened in flagrante or not.

[43]The expected number of robberies for recurrent robbers, meaning robbers who won't stop robbing banks until caught, when their likelihood of success is $p$ is $\sum_{\tau=1}^{\infty} p^{\tau}$.

expected number of robberies would drop from 6.1 to 5.6. Given that there are about 260 first time robbers each year, that 1/3 of these are recurrent offenders, and that the average haul is close to 2,900 euro, the reduction in total haul is approximately equal to 100,000 euro a year (-5 percent). The change is small but could become much larger if criminals started exploiting these inefficiencies.

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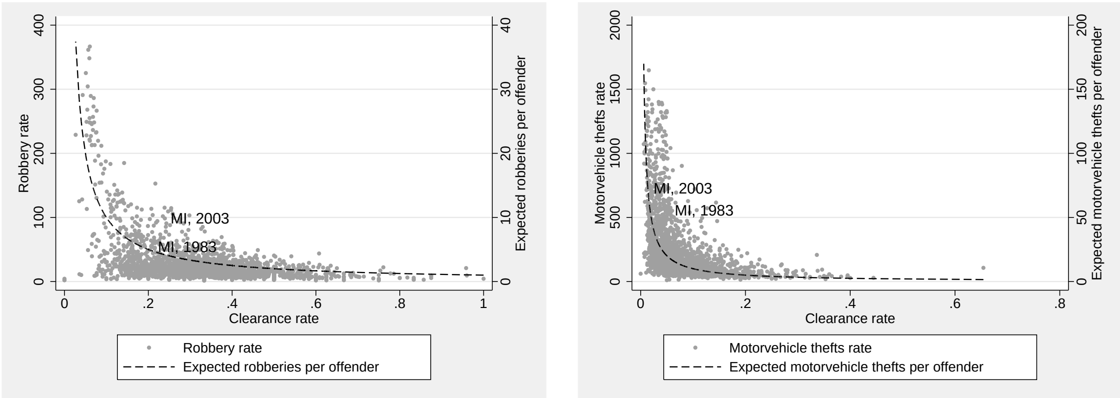


Figure 1: Aggregate Robbery Rates and MV Theft Rates vs. Their Clearance Rates

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

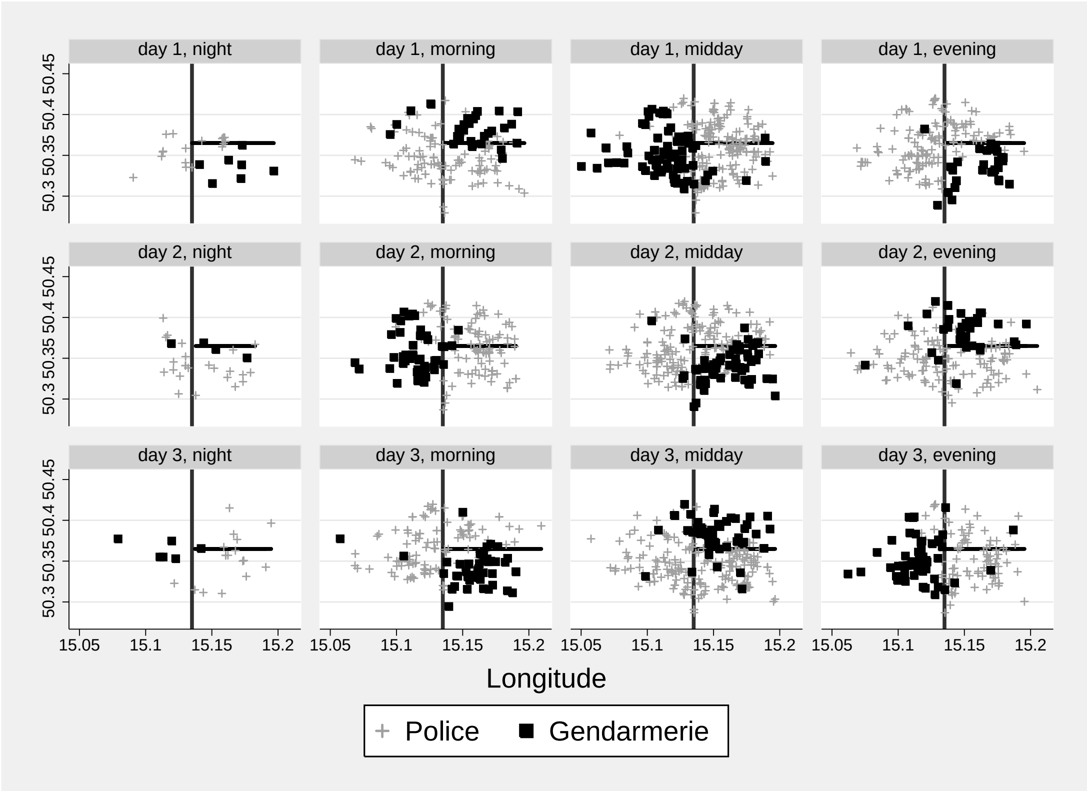


Figure 2: Geographic Distribution of Robberies by Group

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

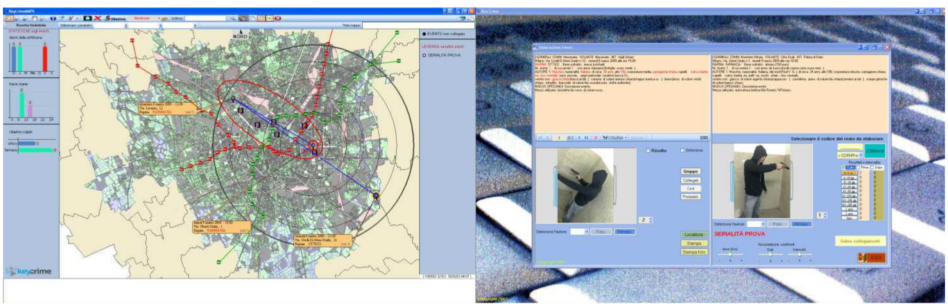

Figure 3: Comparison of Events

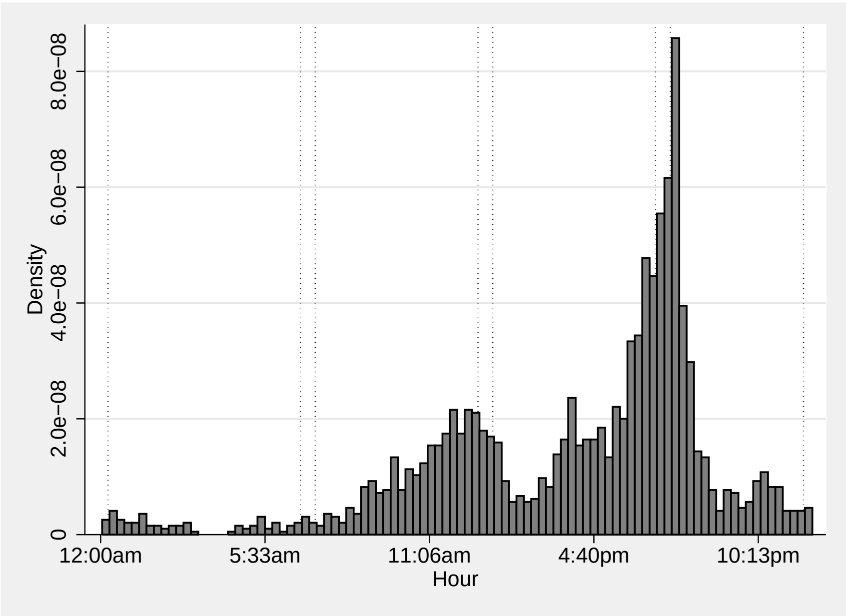


Figure 4: Distribution of Robberies

Notes: The histogram uses 15 minute bins. Vertical lines indicate the 30-minute turnover periods around shifts.

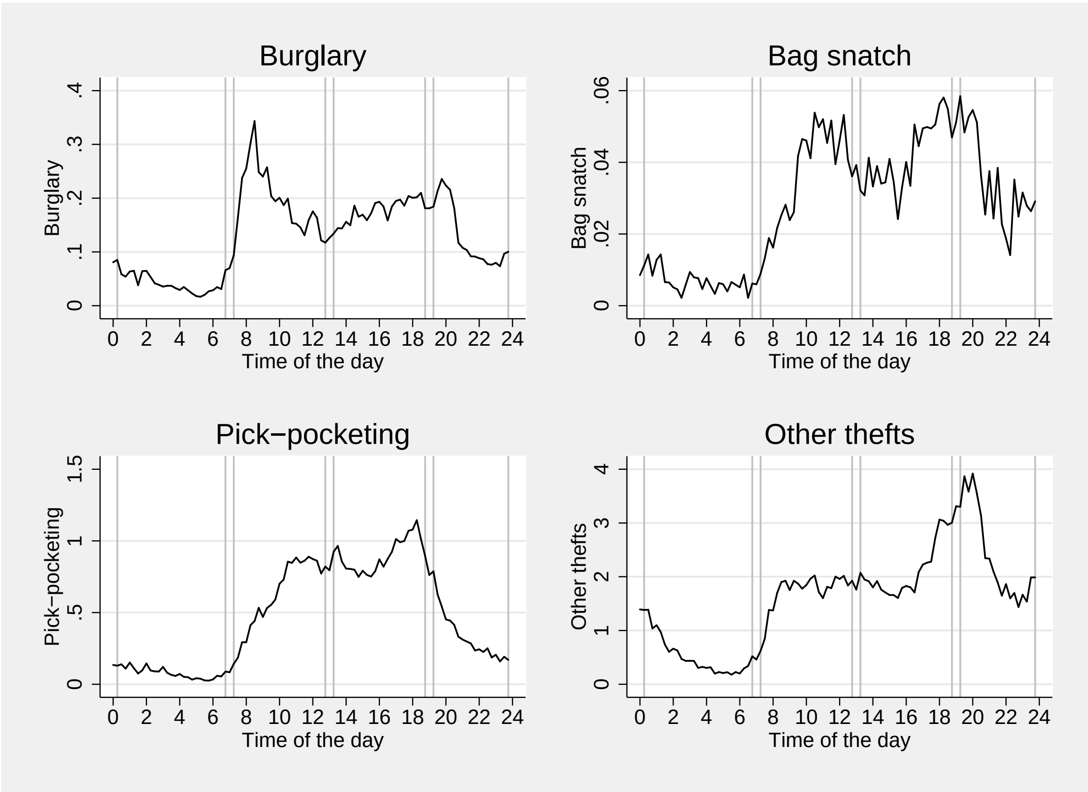


Figure 5: Average Number of Daily Thefts in 15 Minute Intervals

Notes: Based on 93 percent of all thefts that occurred in in Milan between 2009 and 2010. 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 30-minute turnover periods around shifts.

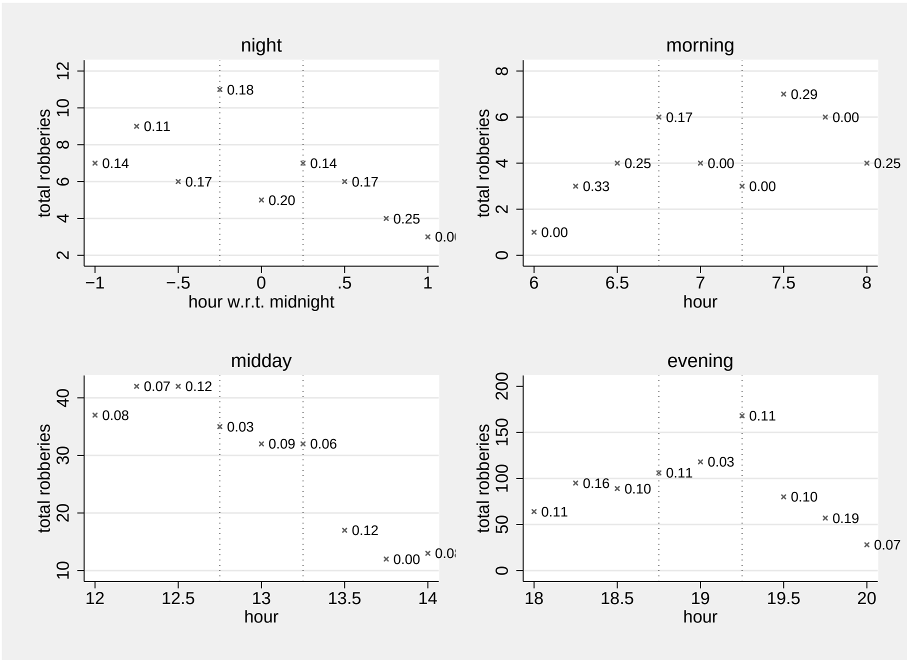


Figure 6: Distribution of Robberies Every 15 Minutes

Notes: Each dot represents the average clearance rate over the following 15 minutes period. Vertical lines indicate the 30 minute turnover periods around shifts. The labels show the corresponding clearance rates.

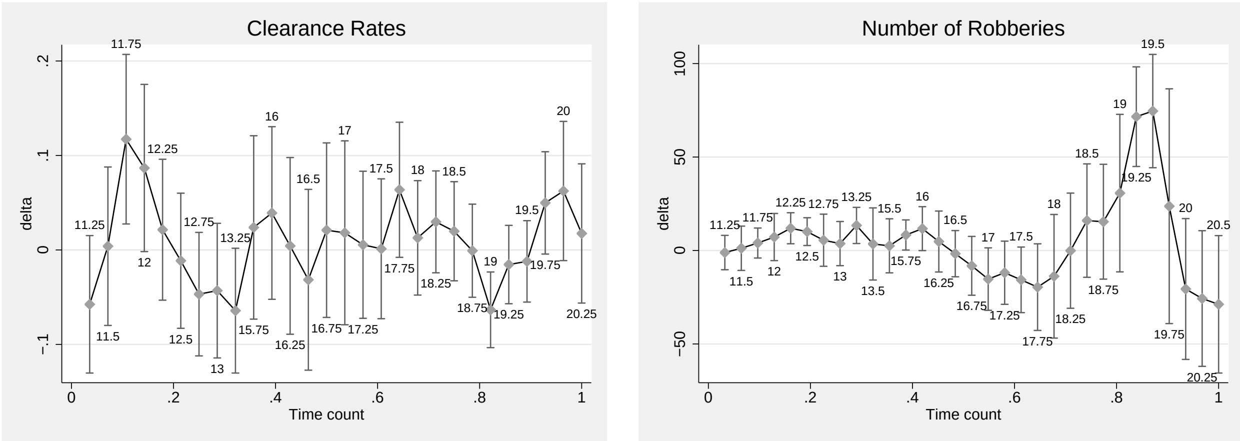


Figure 7: Placebo Test of Turnover Effects

Notes: The horizontal lines indicate the 95 percent confidence intervals around the different $\delta$s. For clearance rates (number of robberies) to preserve some power 30 minute intervals where the robberies (the number of robberies) during the placebo treatments are at least equal to 3 percent (25). For the number of robberies to The $\delta$s are ordered from the lowest to the largest and the labels indicate the corresponding 30 minutes that are treated. Three hours around the treated period represent the control period. The 13.25 estimate, for example, takes the 11.15am-3.15pm period and computes a treatment effect for the 1pm-1.30pm period.

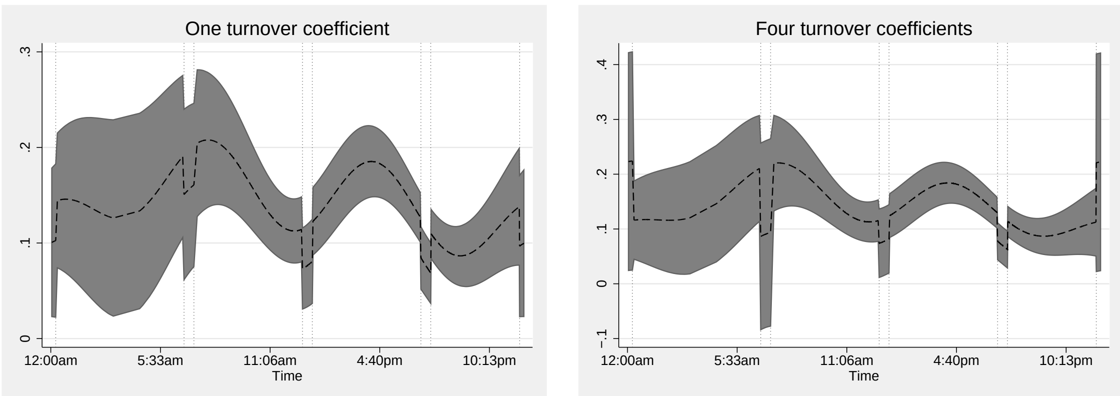


Figure 8: Predicted Clearance Rates

Notes: Vertical lines indicate the 30 minute turnover periods around shifts.

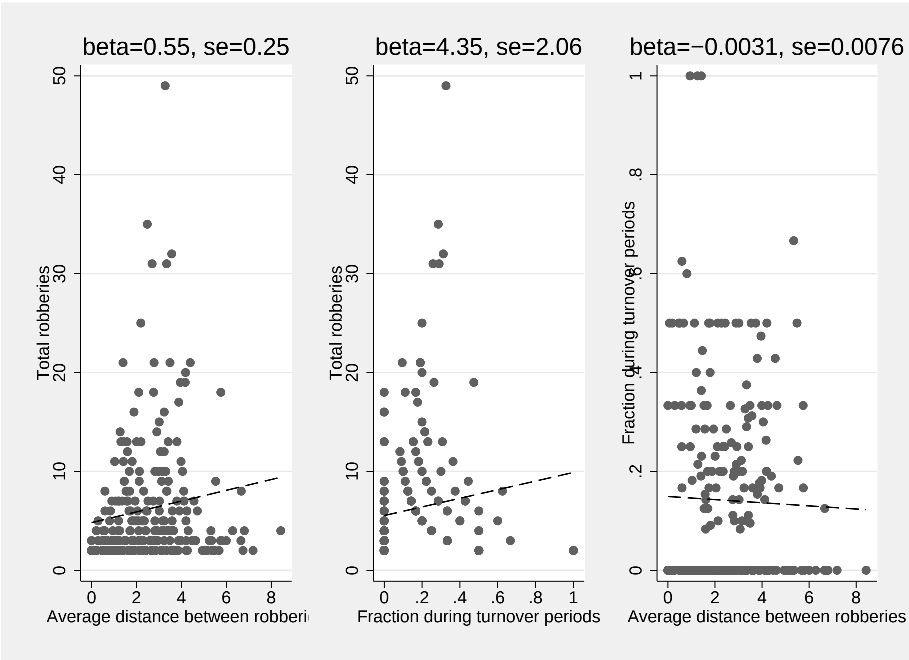


Figure 9: Unpredictability, Success, and Turnover Periods

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 turnover periods is 0.14 (sd=0.20).

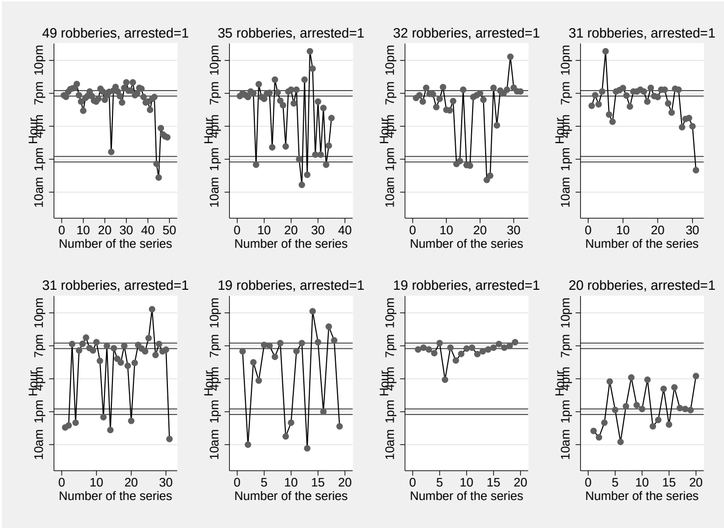


Figure 10: Individual Time Patterns

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

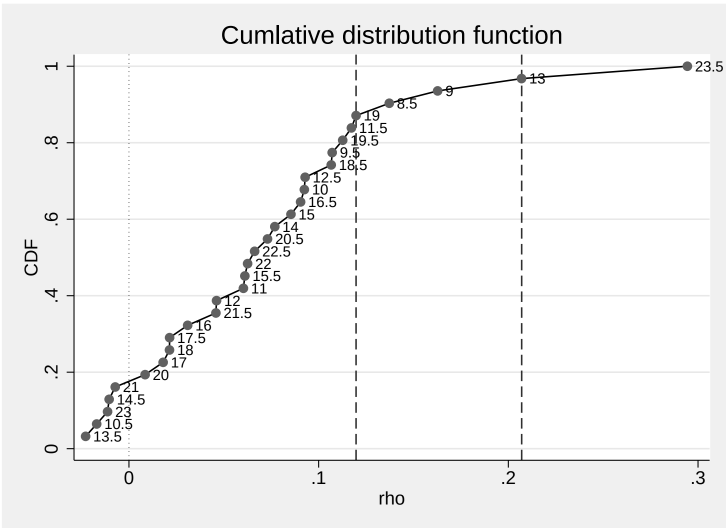


Figure 11: Permutation Test of Persistence

Notes: The figure shows the density and the cumulative distribution function of the 31 different estimates of persistence ($\rho$) one gets using different 30 minute periods between 8.15am and 11.15pm (during the night there are too few robberies to estimate $\rho$). Persistence is estimated using the following autoregressive models $h_n = \rho h_{n-1} + e_n$ over the entire sample.

Table 1: Summary statistics

| Variable | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| Cleared robbery | 0.128 | 0.334 | 0 | 1 |
| Cleared series | 0.564 | 0.496 | 0 | 1 |
| Number of the series | 5.045 | 6.658 | 1 | 49 |
| Police 0/1 | 0.732 | 0.443 | 0 | 1 |
| Shift turnover 0/1 | 0.163 | 0.369 | 0 | 1 |
| Persistent shift 0/1 | 0.348 | 0.476 | 0 | 1 |
| Western area | 0.434 | 0.496 | 0 | 1 |
| North-eastern area | 0.219 | 0.413 | 0 | 1 |
| Distance from the headquarters (in kilometers) | 5.791 | 2.301 | 0 | 15 |
| Distance from the headquarters (in minutes) | 14.213 | 4.532 | 1 | 30 |
| Year | 2009.239 | 1.021 | 2008 | 2011 |
| Month | 5.878 | 3.717 | 1 | 12 |
| Day of the month | 15.6 | 8.862 | 1 | 31 |
| Day of the week | 3.235 | 1.826 | 0 | 6 |
| Shift | 3.024 | 0.837 | 1 | 4 |
| Age | 31.247 | 7.785 | 16 | 68 |
| Amount stolen in euros | 2857 | 11192 | 0 | 206000 |
| Firearm 0/1 | 0.444 | 0.479 | 0 | 1 |
| Foreigner 0/1 | 0.171 | 0.356 | 0 | 1 |
| Number of robbers | 1.57 | 0.716 | 1 | 7 |
| N | | 2164 | | |

Table 2: 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.

Table 3: Simple Difference in Clearance Rates

| | *Clearance rate* | $\delta = (1) - (0)$ | se($\delta$) | N.obs |
|---|---|---|---|---|
| | *Panel A: Clearance rates by turnover* | | | |
| No turnover (0) | 0.137 | | | 1812 |
| Turnover (1) | 0.080 | -0.058 | 0.017 | 352 |
| | *Panel B: Clearance rates across turnovers* | | | |
| No turnover (0) | 0.137 | | | 1812 |
| Morning turnover (1) | 0.091 | -0.047 | 0.087 | 11 |
| Midday turnover (1) | 0.078 | -0.059 | 0.032 | 77 |
| Evening turnover (1) | 0.069 | -0.068 | 0.018 | 246 |
| Midnight turnover (1) | 0.224 | 0.086 | 0.098 | 18 |
| Total | | | | 2164 |

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 turnover dummy.

Table 4: Difference in Clearance Rates

| | (1) | (2) |
|---|---|---|
| | Clearance rate | |
| Sample: | 9.15am-9.15pm | full |
| Time dummies: | | |
| 9.15am to 10.45 am | - | - |
| 10.46am to 11.15am | -0.009 | 0.002 |
| | (0.057) | (0.054) |
| 11.16am to 11.45am | 0.055 | 0.066 |
| | (0.057) | (0.054) |
| 11.46am to 12.15pm | 0.054 | 0.064 |
| | (0.052) | (0.048) |
| 12.16pm to 12.45pm | -0.047 | -0.036 |
| | (0.041) | (0.037) |
| *12.46pm to 1.15pm* | *-0.065* | *-0.054* |
| | *(0.043)* | *(0.039)* |
| 1.16pm to 1.45pm | -0.073 | -0.062 |
| | (0.046) | (0.043) |
| 1.46pm to 2.45pm | - | - |
| 2.46pm to 3.15pm | 0.015 | 0.026 |
| | (0.053) | (0.051) |
| 3.16pm to 3.45pm | - | - |
| 3.46pm to 4.15pm | 0.112** | 0.123** |
| | (0.052) | (0.049) |
| 4.16pm to 4.45pm | 0.015 | 0.026 |
| | (0.051) | (0.049) |
| 4.46pm to 5.15pm | 0.012 | 0.023 |
| | (0.053) | (0.050) |
| 5.16pm to 5.45pm | -0.010 | 0.001 |
| | (0.044) | (0.040) |
| 5.46pm to 6.15pm | 0.003 | 0.014 |
| | (0.039) | (0.035) |
| 6.16pm to 6.45pm | -0.018 | -0.008 |
| | (0.036) | (0.031) |
| *6.46pm to 7.15pm* | *-0.069*** | *-0.059*** |
| | *(0.031)* | *(0.026)* |
| 7.16pm to 7.45pm | -0.049 | -0.039 |
| | (0.030) | (0.025) |
| 7.46pm to 8.15pm | -0.001 | 0.010 |
| | (0.046) | (0.043) |
| 8.16pm to 8.45pm | -0.063 | -0.053 |
| | (0.049) | (0.046) |
| 8.46pm to 9.15pm | - | - |
| Constant | 0.154*** | 0.143*** |
| | (0.023) | (0.015) |
| Observations | 1,875 | 2,164 |
| R-squared | 0.016 | 0.014 |

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. There are no controls other than the constant term and the 30 minute time dummies.

Table 5: Turnover and Outcomes

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Dependent var. / Sample:* | 5.30pm-8.30pm | 6pm-8pm | 6.15pm-7.45pm | 2h intervals for all shifts | whole sample |
| | | | Panel A: Dependent variable is the **Main Outcome** | | |
| Cleared | -0.063*** | -0.059*** | -0.056** | -0.049*** | -0.041** |
| | (0.020) | (0.021) | (0.023) | (0.018) | (0.017) |
| | | | Panel B: Dependent variables are the **Other Regressors** | | |
| Age | -0.063 | 0.198 | 0.392 | 0.045 | 0.312 |
| | (0.498) | (0.497) | (0.533) | (0.461) | (0.437) |
| Haul | -164.263 | -174.333 | -274.184 | 627.620 | 851.579 |
| | (184.581) | (197.872) | (231.162) | (1,123.349) | (1,035.259) |
| Firearm | -0.029 | -0.022 | -0.027 | -0.026 | -0.024 |
| | (0.038) | (0.040) | (0.041) | (0.034) | (0.032) |
| Foreigner | 0.020 | 0.020 | 0.027 | 0.003 | -0.002 |
| | (0.027) | (0.027) | (0.026) | (0.023) | (0.022) |
| Number of robbers | 0.074 | 0.060 | 0.058 | 0.014 | 0.051 |
| | (0.047) | (0.047) | (0.048) | (0.046) | (0.041) |
| Police | 0.012 | 0.009 | -0.000 | -0.000 | 0.006 |
| | (0.034) | (0.036) | (0.036) | (0.029) | (0.026) |
| Western q. | -0.018 | -0.035 | -0.037 | -0.036 | -0.019 |
| | (0.033) | (0.034) | (0.036) | (0.031) | (0.030) |
| North-eastern q. | 0.013 | 0.018 | 0.021 | 0.046 | 0.026 |
| | (0.031) | (0.031) | (0.032) | (0.029) | (0.027) |
| Day of the week | -0.101 | -0.086 | -0.053 | -0.017 | -0.016 |
| | (0.141) | (0.144) | (0.146) | (0.122) | (0.118) |
| N. of observations | 948 | 806 | 679 | 1148 | 2164 |

Notes: The dependent variables are listed in the first column. Each coefficient shown refers to a different regression and measures the effect of a turnover period. Linear models with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The regressions in the last column control for 3 sine and 3 cosine functions of time.

Table 6: Choice of Sine and Cosine Terms

| sin/cos terms | $\delta$ | se | log-likelihood | df | CV MSE | AIC |
|---|---|---|---|---|---|---|
| 1 | -0.054 | 0.017*** | -692.235 | 4 | 0.111411 | 1392.47 |
| 2 | -0.052 | 0.017*** | -687.895 | 6 | 0.111195 | 1387.791 |
| 3 | -0.041 | 0.017** | -684.782 | 8 | 0.111099 | 1385.563 |
| 4 | -0.042 | 0.019** | -684.745 | 10 | 0.111323 | 1389.49 |
| 5 | -0.043 | 0.019** | -683.548 | 12 | 0.111432 | 1391.096 |
| 6 | -0.048 | 0.019** | -681.362 | 14 | 0.111435 | 1390.724 |
| 7 | -0.047 | 0.020** | -681.238 | 16 | 0.111658 | 1394.476 |
| 8 | -0.034 | 0.021 | -678.881 | 18 | 0.111627 | 1393.762 |
| 9 | -0.033 | 0.022 | -678.707 | 20 | 0.111836 | 1397.414 |

Notes: Each line represents a different regression. $\delta$ measures the turnover 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 7: Heterogeneity and Other Controls

| | (1) | (2) | (5) |
|---|---|---|---|
| | Clearance rates | | |
| Shift turnover 0/1 | -0.045** | | |
| | (0.019) | | |
| Turnover × non-smooth | | -0.049** | |
| | | (0.022) | |
| Turnover × smooth | | -0.035 | |
| | | (0.032) | |
| Smooth shift turnover 0/1 | | -0.028 | |
| | | (0.019) | |
| Turnover × Above median time from Police Office | | | -0.063** |
| | | | (0.027) |
| Turnover × Below median time from Police Office | | | -0.024 |
| | | | (0.026) |
| Below median time from Police Office | | | -0.031* |
| | | | (0.017) |
| Number of the series | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| Police 0/1 | 0.040** | 0.051*** | 0.038** |
| | (0.016) | (0.017) | (0.016) |
| Shops' closing time 0/1 (90th percentile) | -0.002 | -0.002 | -0.000 |
| | (0.024) | (0.024) | (0.024) |
| Shops' closing time 0/1 (maximum) | 0.030 | 0.030 | 0.028 |
| | (0.030) | (0.030) | (0.030) |
| Western area | -0.041** | -0.041** | -0.037** |
| | (0.017) | (0.017) | (0.017) |
| North-Eastern area | -0.027 | -0.028 | -0.032 |
| | (0.020) | (0.020) | (0.020) |
| Foreigner 0/1 | 0.002 | 0.003 | 0.003 |
| | (0.020) | (0.020) | (0.020) |
| Number of robbers | -0.022* | -0.021* | -0.022** |
| | (0.011) | (0.011) | (0.011) |
| Constant | 0.522* | 0.509* | 0.511* |
| | (0.308) | (0.307) | (0.306) |
| Observations | 2,164 | 2,164 | 2,164 |
| R-squared | 0.023 | 0.024 | 0.025 |

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. Each regression controls for 3 sine and 3 cosine functions of time, for a cubic in age, and for day of the week, and year dummies.

Table 8: Number of Robberies and Turnover Periods

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Number of robberies | | | | | | | |
| *Sample:* | 2 h interval | 12pm-2pm | 6pm-8pm | Fourier | 2 h interval | 12pm-2pm | 6pm-8pm | Fourier |
| Turnover × non-smooth | 0.835 | -0.076 | 2.390** | 1.643*** | | | | |
| | (0.798) | (0.474) | (1.079) | (0.549) | | | | |
| Turnover × smooth | 0.860 | 0.444 | 3.378*** | 1.965*** | | | | |
| | (0.974) | (0.408) | (1.133) | (0.570) | | | | |
| Smooth shift turnover 0/1 | -0.024 | -0.187 | 0.067 | 0.034 | | | | |
| | (0.417) | (0.341) | (0.662) | (0.144) | | | | |
| Turnover × Above median distance from Police Office | | | | | 0.812 | 0.426 | 2.390*** | 1.669*** |
| | | | | | (0.653) | (0.338) | (0.649) | (0.340) |
| Turnover × Below median distance from Police Office | | | | | 0.939 | -0.250 | 3.134* | 1.919** |
| | | | | | (1.152) | (0.637) | (1.654) | (0.835) |
| Above median distance from Police Office | | | | | -0.413 | -0.454 | -0.494 | -0.218 |
| | | | | | (0.419) | (0.339) | (0.685) | (0.144) |
| Constant | 3.665*** | 2.409*** | 5.156*** | 1.985*** | 3.873*** | 2.583*** | 5.437*** | 2.104*** |
| | (0.264) | (0.214) | (0.436) | (0.080) | (0.351) | (0.283) | (0.594) | (0.105) |
| Observations | 303 | 117 | 151 | 849 | 303 | 117 | 151 | 849 |
| R-squared | 0.007 | 0.005 | 0.048 | 0.299 | 0.011 | 0.019 | 0.053 | 0.301 |

Notes: The dependent variable is the number of robberies that happen in 30 minute intervals. Linear model with robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. “Fourier” regression controls for 3 sine and 3 cosine functions of time.

Table 9: Distribution of Total Robberies and Turnover Periods

| Total robberies | Freq. | CDF | Individual robbers | Median loot | Turnover | Cleared series |
|---|---|---|---|---|---|---|
| 1 | 663 | 0.31 | 663 | 450 | 0.15 | 0.21 |
| 2 | 136 | 0.37 | 68 | 500 | 0.15 | 0.43 |
| 3 | 138 | 0.43 | 46 | 400 | 0.10 | 0.50 |
| 4 | 124 | 0.49 | 31 | 500 | 0.08 | 0.65 |
| 5 | 75 | 0.52 | 15 | 500 | 0.17 | 0.53 |
| 6 | 72 | 0.56 | 12 | 600 | 0.18 | 0.58 |
| 7 | 98 | 0.60 | 14 | 560 | 0.16 | 0.64 |
| 8 | 72 | 0.64 | 9 | 525 | 0.18 | 0.67 |
| 9 | 54 | 0.66 | 6 | 400 | 0.17 | 0.83 |
| 10 | 70 | 0.69 | 7 | 482.5 | 0.16 | 0.71 |
| 11 | 44 | 0.71 | 4 | 675 | 0.20 | 1 |
| 12 | 36 | 0.73 | 3 | 500 | 0.11 | 1 |
| 13 | 91 | 0.77 | 7 | 700 | 0.15 | 0.71 |
| 14 | 28 | 0.79 | 2 | 445 | 0.21 | 0.50 |
| 15 | 15 | 0.79 | 1 | 500 | 0.20 | 0 |
| 16 | 32 | 0.81 | 2 | 205 | 0.00 | 1 |
| 17 | 17 | 0.82 | 1 | 1000 | 0.18 | 0 |
| 18 | 54 | 0.84 | 3 | 935 | 0.09 | 1 |
| 19 | 38 | 0.86 | 2 | 750 | 0.37 | 1 |
| 20 | 20 | 0.87 | 1 | 10500 | 0.20 | 1 |
| 21 | 84 | 0.91 | 4 | 465 | 0.17 | 1 |
| 25 | 25 | 0.92 | 1 | 700 | 0.20 | 1 |
| 31 | 62 | 0.95 | 2 | 660 | 0.27 | 1 |
| 32 | 32 | 0.96 | 1 | 600 | 0.31 | 1 |
| 35 | 35 | 0.98 | 1 | 800 | 0.29 | 1 |
| 49 | 49 | 1.00 | 1 | 1100 | 0.33 | 1 |
| Whole sample | 2164 | | | 500 | 0.16 | 0.56 |

Notes: This table shows the distribution of robberies by their total number by group of robbers. For example, there are 663 robbers of group of robbers who appear to have committed just one robbery, while there is one group who has committed 49 robberies (and has 49 observations in the data).

Table 10: Turnover and Clearance Rates Controlling for Ability

| | Method | Sample | Shift turnover 0/1 | | | |
|---|---|---|---|---|---|---|
| | | Turnover history: | $\delta$ | SE | N.obs. | R2 |
| (1) | Simple | Never before | -0.071** | (0.033) | 586 | 0.005 |
| (2) | difference | Some | -0.059*** | (0.022) | 671 | 0.007 |
| (3) | Sine and | Never before | -0.059 | (0.036) | 586 | 0.014 |
| (4) | cosine | Some | -0.055** | (0.023) | 671 | 0.015 |
| (5) | 2h interval | Never before | -0.072* | (0.039) | 279 | 0.009 |
| (6) | | Some | -0.052** | (0.025) | 425 | 0.008 |

Notes: The "Never before" sample deletes observations of robbers once they fall into a turnover period. The identification of the turnover effect is based on robbers who for the first time fall into a turnover period. The "Some" sample has in the past done at least one robbery during a turnover period. Each line corresponds to a different regression. 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 sine and cosine regressions control for 3 sine and 3 cosine functions of time.

Table 11: The Probability of Turnover Periods

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | | Placebo: | |
| Turnover dummies: | Midday | Evening | Any | 30 min later | 30 min earlier |
| Morning turnover (n-1) | -0.033*** | -0.111*** | | | |
| | (0.006) | (0.013) | | | |
| Midday turnover (n-1) | 0.184*** | -0.089*** | | | |
| | (0.062) | (0.026) | | | |
| Evening turnover (n-1) | -0.021** | 0.128*** | | | |
| | (0.010) | (0.033) | | | |
| Night turnover (n-1) | -0.033*** | -0.111*** | | | |
| | (0.006) | (0.013) | | | |
| Any turnover (n-1) | | | 0.080*** | | |
| | | | (0.030) | | |
| 30 min later (n-1) | | | | 0.065* | |
| | | | | (0.038) | |
| 30 min earlier (n-1) | | | | | 0.191*** |
| | | | | | (0.034) |
| Observations | 1,257 | 1,257 | 1,257 | 1,257 | 1,257 |
| R-squared | 0.037 | 0.022 | 0.007 | 0.004 | 0.035 |

Notes: Linear probability models of falling into a given turnover period with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The sample is based on robbers or group of robbers with at least 2 offenses.

Table 12: Individually Defined Turnover Period

| | (1) | (2) | (3) |
|---|---|---|---|
| | Clearance rates | | |
| | Simple difference | 2h interval | Fourier |
| Turnover effects with | | | |
| $\kappa$=1 | -0.056*** | -0.040** | -0.040** |
| | (0.017) | (0.019) | (0.018) |
| $\kappa = 1.1$ | -0.058*** | -0.043** | -0.042** |
| | (0.017) | (0.018) | (0.018) |
| $\kappa = 1.2$ | -0.061*** | -0.046** | -0.045*** |
| | (0.016) | (0.018) | (0.017) |
| $\kappa = 1.3$ | -0.061*** | -0.047*** | -0.045*** |
| | (0.016) | (0.018) | (0.017) |
| $\kappa = 1.4$ | -0.053*** | -0.038** | -0.036** |
| | (0.016) | (0.018) | (0.017) |
| $\kappa = 1.5$ | -0.053*** | -0.038** | -0.036** |
| | (0.015) | (0.018) | (0.017) |
| Observations | 2164 | 1173 | 2164 |

Notes: Each coefficient measures the effect of a turnover period and refers to a different regression. These estimates exploit information on the exact location of the incident, and Google's predicted duration $\tau$ of driving from the gendarmerie or the police 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: $Y_{i,n} = \alpha + \delta I(|t_{i,n} - T| \leq \kappa\tau_{i,n}) + \epsilon_{i,n}$. The Fourier regressions control for 3 sine and 3 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 13: Spillovers

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Daily robberies: | first | just one | first | just one |
| | Simple difference | | Fourier | |
| Shift turnover 0/1 | -0.070*** | -0.067** | -0.051** | -0.053* |
| | (0.021) | (0.026) | (0.022) | (0.027) |
| Observations | 1,295 | 747 | 1,295 | 747 |
| R-squared | 0.006 | 0.006 | 0.013 | 0.019 |

Notes: For each day and for each police force the "first" robbery uses a sample where subsequent robberies are excluded. "Just one" uses only robberies where in a given day police forces were subject to at most one robbery. The Fourier regressions control for 3 sine and 3 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.

# A For Online Publication: Appendix

Table 14: 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 15: Turnover Periods

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Dependent variable* | | | Turnover period (0/1) | | |
| Sample: | | full | | total r.>18 | total r.$\leq$18 |
| Number of the series | 0.003** | -0.006*** | -0.006*** | -0.007** | -0.004 |
| | (0.001) | (0.002) | (0.002) | (0.003) | (0.004) |
| Total number of the series | | 0.007*** | | 0.007** | 0.002 |
| | | (0.001) | | (0.003) | (0.003) |
| Individual FE | - | - | $\checkmark$ | - | - |
| Observations | 2164 | 2164 | 2164 | 345 | 1819 |
| R-squared | 0.002 | 0.016 | 0.418 | 0.025 | 0.000 |

Notes: This Table shows regressions of the turnover dummy on the robbery's number of the series. The first robbery has a value 1, the second 2, etc. The sample restrictions in the last two columns depend on the total number of robberies "total r.". Linear probability models with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Turnover Periods

| | Method | Sample | Shift turnover 0/1 | | | |
|---|---|---|---|---|---|---|
| | | | $\delta$ | SE | N.obs. | R2 |
| (1) | Simple | Whole | -0.058*** | (0.016) | 2,164 | 0.004 |
| (2) | difference | Exclude 1pm | -0.060*** | (0.018) | 2,013 | 0.004 |
| (3) | Sine and | Whole | -0.041** | (0.017) | 2,164 | 0.012 |
| (4) | cosine | Exclude 1pm | -0.041** | (0.020) | 2,013 | 0.012 |
| (5) | 2h interval | Whole | -0.049*** | (0.018) | 1,148 | 0.005 |
| (6) | | Exclude 1pm | -0.057*** | (0.021) | 881 | 0.007 |

Notes: The "Exclude 1pm" sample excludes robberies that happen between 12.45pm and 1.15pm. Linear probability model of clearing the case with clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.