Police and Clearance Rates: Evidence from Quasi-Random Redeployment Within a City
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Giovanni Mastrobuoni*

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Abstract

A fair number of recent papers have shown that an increase in the number of police forces reduces crime, but little is know about the mechanism. It is not entirely clear weather police deters crime by reducing the attractiveness of crimes, or whether the reduction is driven by an incapacitation of criminals (Cook et al., 2011, Levitt and Miles, 2004).

This paper exploits quasi-random redeployment of two police forces within the same Italian city, Milan, providing first evidence of incapacitation. A reduction in the number of police forces that patrol the streets leads to lower clearance rates.

Keywords: police, crime
JEL classification codes: H7; H72; H76

*Collegio Carlo Alberto and CeRP, Via Real Collegio 30, Moncalieri, Italy, giovanni.mastrobuoni@carloalberto.org.

1 Introduction

Several recent papers have shown that an increase in the number of police forces reduces crime[1] Despite this, the mechanism of this reduction is still somewhat of black box. Crime might respond to police forces because of two very different reasons, deterrence and incapacitation, which lead to somehow different policy prescriptions. Deterrence, for example, is more likely to generate geographical or temporal spillovers than incapacitation. In other words, if the police reduced crime only through deterrence the effects would be more likely to be short-lived, or at least more geographically restricted. Despite the importance of such a distinction little is know about it. The main reason is that police deployment generally depends on crime, and such endogeneity makes any causal inference hard to achieve.

This paper finds strong evidence of incapacitation exploiting quasi-random redeployment of two police forces within the same Italian city, Milan. Precise information about the exact time and the exact place of the robbery coupled with information about the robbery shows that having less police on the streets during shift turnovers lowers the likelihood of solving a robbery by more than 30 percent. Criminals do not seem to take advantage of shift turnovers.

Skogan and Kathleen Frydl (2004) review the criminology literature on the effectiveness of police. The closest type of studies to this one, are the ones that use police strikes to evaluate the effect of police on crime. What these studies generally find is 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 a sudden lack of deterrence. This paper, instead, shows that during turnovers, that are more difficult to detect or predict, it is not the number of crimes that changes but the arrest rates. Another set of studies

[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).

uses random changes in patrols to test the effectiveness of police, but again the focus is on crime, not on clearance rates (Sherman, 2002).

The only paper that tries to separate incapacitation and deterrence is not related to crime but to sports. McCormick and Tollison (1984) find strong evidence of deterrence: when the number of college basketball referees increased from two to three the number of fouls dropped by more than 30 percent.[2]

2 Random Redeployment

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. During the fascist era Mussolini established a new police force, the *Polizia di Stato* (state police). Up until the end of the 1990s the two police forces were operating side by side, without communicating with each other, with the exception of the countryside were the police does not operate. While the communication aspect has not really changed much, the government decided that to save resources the two forces would divide the main cities into quadrants, and each force would be solely responsible for keeping law and order in a given quadrant. In Milan, for example, the city is divided into three quadrants, two fall under the responsibility of the police and one under the one of the gendarmerie. Thus the police covers an area that is twice as large as the one covered by the gendarmerie.

This division into quadrants alone would not provide random variation because forces could be selected into given zones according to their characteristics. But the assignment of police forces to these quadrants rotate every 6 hours counterclockwise. Given that there are two forces, three quadrants, and four 6-hour shifts within a given day, a given force is

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

going to cover the same quadrant during the same 6-hour shift only every three days. This means that there is quasi-random variation in the days of the month, days of the week, and 6-hour shift in the coverage of police forces. Figure 1 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 gray dot. One can see that in day/time combinations that belong to group 1 the gendarmerie covers the western part of the city while the police covers the northeastern and southeastern part of it. In group 2 day/time combinations the gendarmerie covers the north-eastern part and in group 3 the south-eastern one. The few outliers are driven by cars that are part of smaller police or gendarmerie offices (*commissariati*) that are distributed across the city, by the mobile forces (*squadra mobile*) and the motor bikers that typically operate it the more criminally active places.

In this paper I use turnover of shifts that happen every 6 hours as a measure for a reduction in police forces. Whenever a shift ends the police cars enter the police stations and new crews take the place of the old ones. The Internet has several movies that show these imposing turnover, and Figure 2 shows two snapshots taken from such a turnover. In the left one one can see several police cars that are ready to leave the parking lot of the *Questura*, the main Police station of Rome, during the night shift turnover, while the right one shows the same cars a few seconds later leaving the *Questura*. This means that during the turnover there is a considerable weakening of the city's police control. In a later section I'm going to see whether criminals respond to these turnovers by concentrating their robberies around them.

3 Data and Randomization

3.1 Data

The data 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. The police not only surveys the victims, they 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. I have been given access to a subset of such data, whose 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 crime scenes. The variable "Number of the series" indexes the robberies that are linked with each other in a chronological manner, and the longest series lasted 49 robberies. 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, 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). The "Full coverage" variable indicates whether the police or the gendarmerie have been the sole investigative force of a given series. The gendarmerie has been the sole investigator for 13 percent of the robberies, while the police has been the sole investigator for 44 percent of them. The remaining fraction of robberies has been investigated by both forces. 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 "smooth" turnover variable is equal to one whenever the police covered the quadrant where the robbery happened during the previous shift. Given that there are 2 quadrant out of three that are covered by the police it is not surprising that the fraction of such quadrants is equal to 30 percent. I set the businesses' closing time variable equal to one when the time is between 7.15pm and 8pm, except for banks which close between 3.30pm and 4.15pm. 17.5 percent of all robberies happen around closing hours.

3.2 Randomization check

I'm going to use shift turnover to measure reductions in police. But one needs to understand whether criminals sort into those time frames in order to make sure that changes in clearance rates can only be due to a reduced presence of police forces.

Randomization checks are going to test whether over time of the day there are discontinuities in the distribution of robberies and in their characteristics. The unconditional distribution of robberies is shown in Figure 3. Most robberies happen around late morning or late afternoon when businesses are about to close and might have more cash in their cash registers. But the spike in robberies continues beyond the late-afternoon turnover and there is no clear evidence of bunching during turnovers. Said that, the time of the later afternoon turnover is very unfortunate given the large number of robberies.

Figure 4 shows several predicted values of the following kind of regressions:

$$Y_t = \alpha + \sum_{i=1}^{3} \beta_i T_{it} + \sum_{i=1}^{3} (\gamma_i \cos(i \times 2\pi H_t) + \delta_i \sin(i \times 2\pi H_t)) + \epsilon_t, \tag{1}$$

where the dependent variable Y_t is either the value of the stolen goods, the use of firearms, or the probability of arrest. $T_{it}, i = 1, 2, 3$ indicate the turnovers, and H_t indicates the time of day standardized to lie between 0 (midnight) and 1 (midnight $+\epsilon$). The sine and cosine function allow me, due to their 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 value are the same.

Figure 4 shows the predicted values of Y_t. Overall the average loot, shown in the upper panels, tends to be close to zero during the night, reaches its maximum value early in the morning, has a second peak immediately after lunch time, and then decreases. The left panel shows that when the coefficients on the turnover dummies are constraint to be the same ($\beta_i = \beta$) they are slightly positive with respect to the overall pattern of the average loot. But Column 1 of Table 2 shows that the turnover dummy is equal to 900 euro but is not significantly different from zero. When the coefficients on the turnover dummies are unrestricted the morning turnover dummy is negative and different from zero but the density of the robberies (dotted line) shows that such estimate is based on very little data. The morning and the evening turnover show the most significant reductions, and this is when traffic is very bad and turnover are likely to take longer.

The use of firearms has been shown to be related to the ability of robbers (Mastrobuoni, 2011). But even there Figure 4 shows that the use of firearms does not vary during shift turnovers, indicating again that there seems to be little selection by criminals. Table 3 shows that randomization checks for all the remaining variables, and the fraction of significant coefficients is not larger than 5 percent.

4 Empirical Evidence

The next step is to see whether during shift turnovers reduced police presence leads to lower clearance rates. Table 2, columns 5 and 6, indicate that clearance rates are on average 5 percentage points lower during turnovers, which corresponds to a 31 percent reduction. And Figure 5 shows that only during night turnovers, where due to the lack of traffic turnovers are likely to be much faster, there is no reduction in clearance rates. Lower clearance rates lead to additional robberies. The lower panels of Figure 5 show that the number of robberies that are linked to a specific series is the mirror-image of the clearance rates. One might think that is result is driven by more able robbers who systematically organize their robberies around shift turnovers. To analyze this possibility I estimate the hour expected time of the robbery as a function of the time chosen in the previous one, interacted with the lagged turnover dummy. Table 4 shows that robbers tend to stick to specific times of the day. The lagged time has a coefficient of 40 percent, a decent degree of stickiness. But criminals that happened to organize the previous robbery during a turnover do not stick even more to that specific time. The opposite is true for criminals who organized their robbery during closing time (Column 2): they tend to systematically target that time. The interaction term the autoregressive coefficient is almost equal to one.

Finally Table 5 shows that the results do not change when one controls for a large number of controls, namely year, month, day, and day of the week dummies, a police dummy, quadrant dummies, foreigner dummies, shops closing time dummies, a cubic in age, and the number of robberies. 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 software that tries to predict robberies. The south-eastern quadrant of the city has higher clearance rates, and so do the robbery that happen during businesses closing times. Robberies organized by foreigners are more easily cleared, as are robberies organized by smaller groups. Age of the robbers does not seem to matter much.

5 Conclusions

Using precise micro-level information about robberies against businesses coupled with some peculiar shift-turnover rules I show that police leads to higher clearance rates. The effect does not seem to be driven by more able criminals targeting businesses during shift turnovers. Since the data do not measure the reduction in policing during turnovers I cannot estimate the elasticity but the morning and the evening turnover which happen when traffic is very bad show the largest reduction in clearance rates. This suggests that faster turnovers reduce the inefficiency.

On simple policy advice to reduce the inefficiency would be to have the shift turnover on the streets instead of at the central police station. An alternative one would be to have patrol-specific shift turnovers to avoid times when almost no police cars are on patrol.

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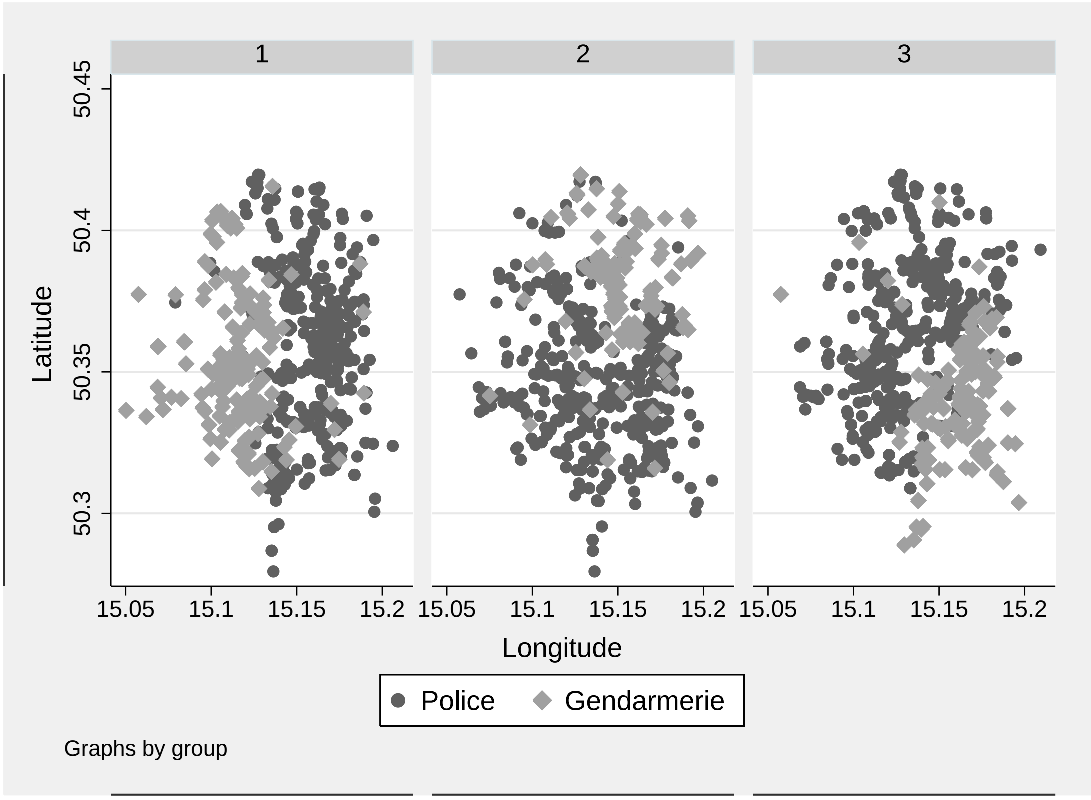

Figure 1: Geographic Distribution of Robberies by Group

Notes: Groups are defined based on the exact day and time of a robbery.

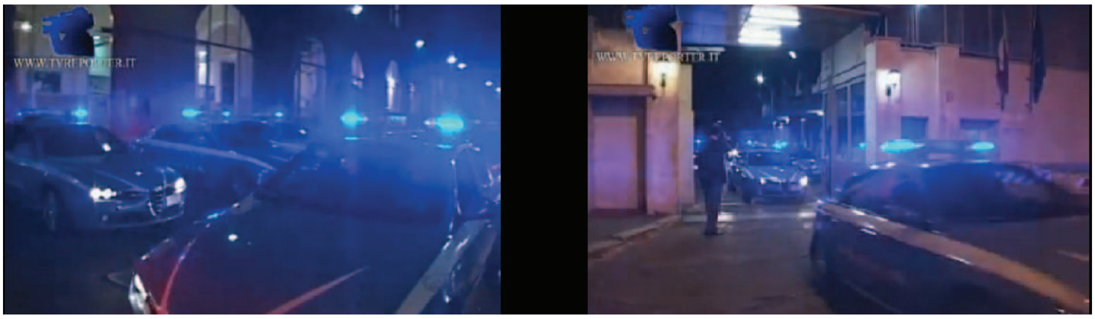

Figure 2: Night Shift Turnover

Notes: The picture refers to Rome's police night shift turnover. The movie is available on YOUTUBE at `http://www.youtube.com/watch?v=3gFYDSi25w8`.

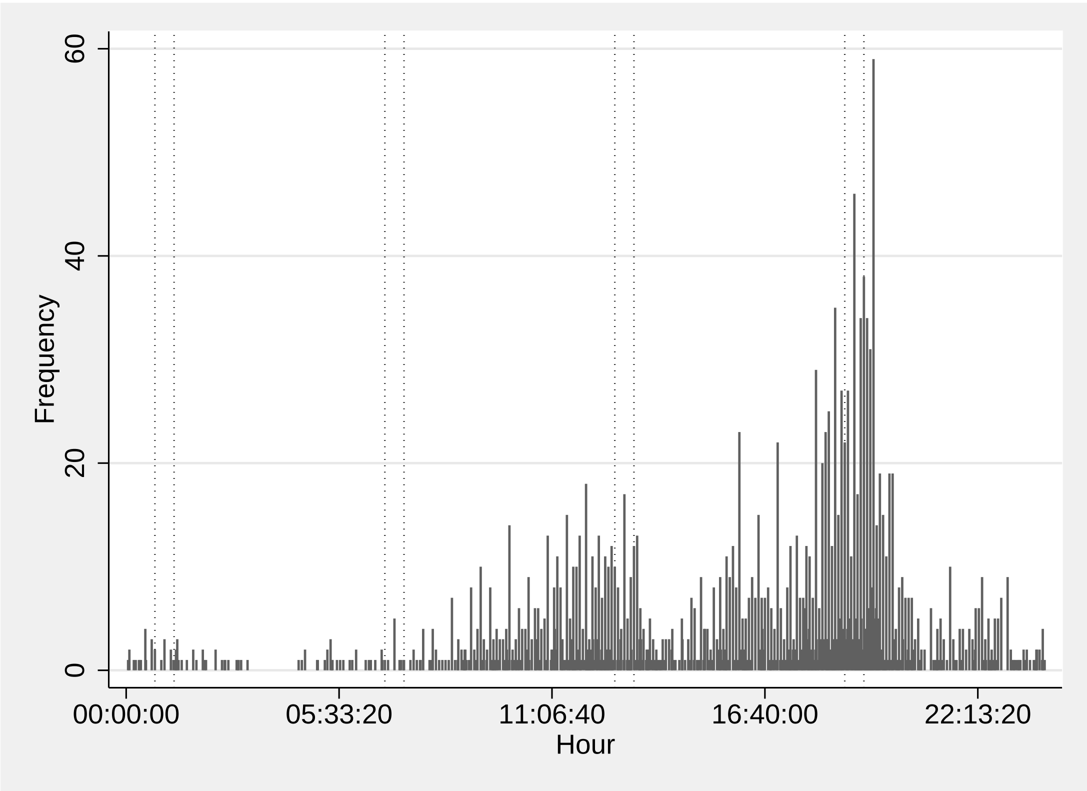

Figure 3: Distribution of Robberies by Time

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

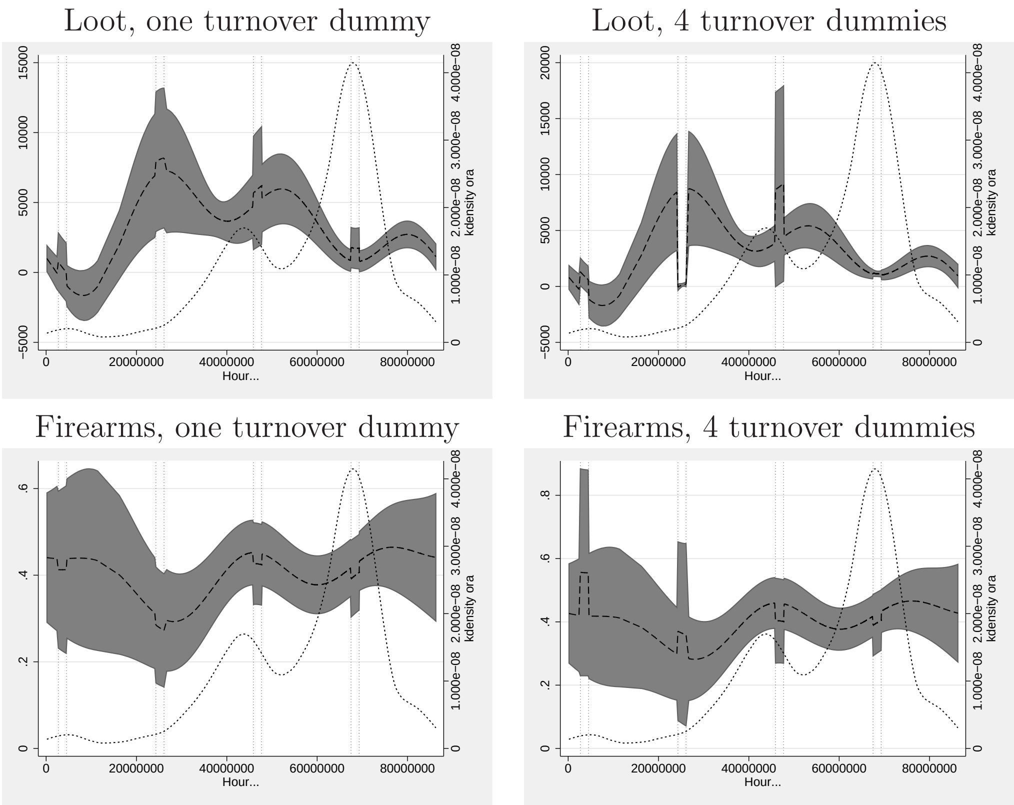

Figure 4: Loot, Use of Firearms over Time

Notes: Vertical lines indicate the 30 minute turnover periods around shifts. The dotted line shows the density of robberies.

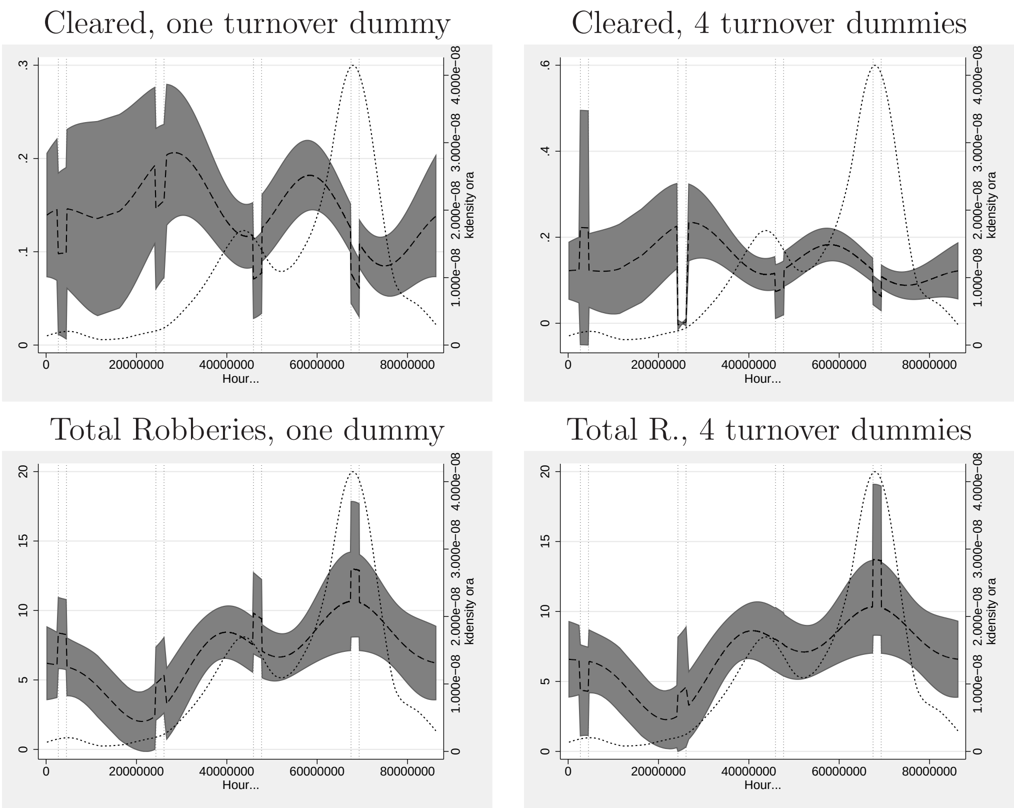

Figure 5: Clearance Rates and Total Robberies over Time

Notes: Vertical lines indicate the 30 minute turnover periods around shifts. The dotted line shows the density of robberies.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Cleared robbery	0.127	0.333	0	1
Cleared series	0.527	0.499	0	1
Number of the series	5.045	6.658	1	49
Carabinieri=0, Police=1	0.732	0.443	0	1
Full coverage Gendarmerie 0/1	0.131	0.337	0	1
Full coverage Police 0/1	0.444	0.497	0	1
Shift turnover 0/1	0.159	0.365	0	1
Smooth shift turnover 0/1	0.3	0.459	0	1
Western quadrant	0.434	0.496	0	1
North-eastern quadrant	0.219	0.413	0	1
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	2.167	0.804	1	4
Shops' closing time 0/1	0.175	0.38	0	1
Age	31.243	7.792	16	68
Amount stolen in euros	2857.536	11192.277	0	206000
Firearm 0/1	0.412	0.492	0	1
Foreigner 0/1	0.23	0.421	0	1
Number of robbers	1.57	0.716	1	7
N		2164		

Table 2: Turnover and Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loot		Firearm		Cleared		Total Robberies	
Turnover	932.328		-0.026		-0.048***		2.307***	
	(1,077.442)		(0.033)		(0.017)		(0.819)	
Morning Turnover		-8,570.457***		0.073		-0.231***		1.551
		(2,666.888)		(0.168)		(0.048)		(1.593)
Lunch Turnover		4,768.018		-0.056		-0.043		0.047
		(4,254.566)		(0.072)		(0.037)		(0.985)
Evening Turnover		96.135		-0.028		-0.046**		3.356***
		(235.249)		(0.040)		(0.021)		(1.233)
Night Turnover		1,699.768*		0.136		0.099		-2.152
		(982.262)		(0.178)		(0.143)		(1.824)
Observations	2164	2164	2164	2164	2164	2164	2,164	2,164
R-squared	0.028	0.035	0.005	0.006	0.012	0.013	0.041	0.043

Notes: Each regression controls for very flexible sine and cosine functions of time. Clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Turnover and Several Other Outcomes

	(1) Police	(2) Western q.	(3) N.East q.	(4) Year	(5) Month	(6) Day	(7) Day week	(8) Age	(9) Foreigner	(10) N. criminals
					Panel A: Constraint coefficients					
Turnover	0.002	-0.025	0.032	0.056	0.318	-0.378	-0.082	0.354	-0.001	0.038
	(0.027)	(0.030)	(0.028)	(0.063)	(0.228)	(0.545)	(0.115)	(0.443)	(0.026)	(0.042)
Observations	2,164	2,164	2,164	2,164	2,164	2,164	2,164	2,164	2,164	2,164
R-squared	0.003	0.006	0.006	0.008	0.008	0.003	0.011	0.046	0.009	0.014
					Panel B: Unconstraint coefficients					
Morning Turnover	0.139	-0.006	-0.003	-0.164	2.165*	3.608	0.394	1.421	-0.016	-0.274
	(0.139)	(0.158)	(0.128)	(0.296)	(1.216)	(2.779)	(0.632)	(2.730)	(0.148)	(0.231)
Lunch Turnover	-0.038	-0.040	0.092	0.089	-0.058	-0.188	-0.071	0.765	-0.055	-0.039
	(0.054)	(0.071)	(0.075)	(0.120)	(0.467)	(1.219)	(0.227)	(1.050)	(0.048)	(0.111)
Evening Turnover	0.010	-0.015	0.010	0.086	0.380	-0.882	-0.083	0.123	0.017	0.102**
	(0.034)	(0.033)	(0.031)	(0.080)	(0.287)	(0.689)	(0.143)	(0.507)	(0.032)	(0.047)
Night Turnover	-0.038	-0.154	0.098	-0.544	-0.403	3.946	-0.689	0.930	0.013	-0.356*
	(0.144)	(0.169)	(0.144)	(0.347)	(1.277)	(2.848)	(0.799)	(1.862)	(0.172)	(0.200)
Observations	2,164	2,164	2,164	2,164	2,164	2,164	2,164	2,164	2,164	2,164
R-squared	0.004	0.006	0.007	0.009	0.009	0.005	0.012	0.047	0.010	0.017

Notes: Each regression controls for very flexible sine and cosine functions of time. Clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Habits and Time of the Robbery

	(1)	(2)
	Time	
lagged Time	0.403***	0.383***
	(0.054)	(0.056)
lagged Time x Turnover	-0.094	
	(0.097)	
Turnover	1.810	
	(1.743)	
lagged Time x Closing Time		0.511***
		(0.178)
Closing Time		-9.378***
		(3.201)
Observations	1,257	1,257
R-squared	0.148	0.150

Notes: Clustered (by series) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Turnover and Outcomes

	(1)	(2)
	Cleared	
Turnover	-0.035**	
	(0.017)	
Morning Turnover		-0.250***
		(0.055)
Lunch Turnover		-0.027
		(0.037)
Evening Turnover		-0.032
		(0.021)
Night Turnover		0.074
		(0.140)
Police 0/1	0.038**	0.039**
	(0.015)	(0.015)
Western quadrant	-0.034**	-0.034**
	(0.016)	(0.016)
North-eastern quadrant	-0.034*	-0.034*
	(0.019)	(0.019)
Foreigner 0/1	0.050***	0.051***
	(0.019)	(0.019)
Age	-0.017	-0.017
	(0.022)	(0.022)
Age squared	0.001	0.001
	(0.001)	(0.001)
Age cube	-0.000	-0.000
	(0.000)	(0.000)
Number of robbers	-0.018	-0.018*
	(0.011)	(0.011)
Shops' closing time 0/1	0.044**	0.043*
	(0.022)	(0.022)
Observations	2,164	2,164
R-squared	0.047	0.049

Notes: Each regression controls for very flexible sine and cosine functions of time, for year, month, day, and day of the week dummies. Clustered (by series) standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.