Criminal Careers and Criminal Firms [1]

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Chapter 1

Introduction

This study presents new evidence on that nature of criminal careers. Criminologists have studied and described "criminal careers" for over 80 years, beginning with 500 Criminal Careers, the landmark 1930 Glueck and Glueck study documenting the lives of the residents of a Massachusetts juvenile reform school.

Our view of criminal careers differs from this long standing and esteemed research, much of which builds on Blumstein et al. (1986) and is recently reviewed in Piquero et al. (2013), in the sense that we will use the framework of labor economics to provide structure to our description of men who engage in robbery in Milan during the early 2000s.

Our approach builds on the field of the "Economics of Crime" (Becker, 1968), where criminal behavior is assumed to respond to incentives, much like the behavior of workers and firms. This does not imply that only incentives matter; sociological and psychological factors are likely to matter as well but are not going to be discussed in this study. The contribution of this chapter follows from the comparative advantage that economists have in the quantitative analysis of large data sets derived from administrative records, as well as a clear understanding of concepts like endogeneity, causality, efficiency, incentives, opportunity cost, and general equilibrium.

The questions we shed light on are also classics in economics: what is the relationship between age, nationality, or education and labor market entry, job mobility, or retirement? How do periods of unemployment affect future labor market activity? Does experience increase human capital, or are their simply high and low quality workers? We will use economic and econometric reasoning to think about recidivism and victim selection, and will also compare the distribution and productivity of "firms" in the robbery industry with basic facts about "legal firms" in the United States.

The ultimate goal of our efforts is to derive sound policy implications that might improve the social wellbeing. There are four social "goods" that are derived from arrest, conviction, and incarceration. First, punishment deters potential criminals by increases the cost associated with criminal behavior. Second, incarceration in particular can physically prevent crime by removing offenders from society. Third, the experience of punishment can have a specific deterrent effect on established criminals, causes them to update their beliefs about the disutility associated with future punishments. Finally, knowing that a criminal has been punished provides non-criminal members of society with a sense of justice or, less diplomatically, vengeance for the committed offenses. In addition to describing the anatomy of criminal careers in Milan, we will also evaluate the extent to which governments in Milan are allocating their scarce resources in a way that achieves these goals.

We address these old questions in economics and criminology in a new way, using two sources of administrative data from criminal justice agencies in Milan- the *Questura di Milano* and records of *Dipartimento di Amministrazione Penitenziaria*. Both data sources are used to highlight observed characteristics of robbers, and their robberies, that are associated with particularly destructive and socially harmful offenses, and also what characteristics are associated with harsher punishments. If judges assigned sentences in such a way that, in equilibrium, equated the marginal benefit of crime to its marginal cost, we would expect that characteristics that are associated with costly robberies are also associated with harsher punishments.

Tracking the patterns of punishment and recidivism over time in the corrections data reveals an intriguing non-monotonic relationship between sentence length and behavior. In particular, we find that individuals who are early in their criminal careers are more likely to recidivate if they receive longer sentences. However, among more experienced criminals, longer sentences are associated with lower rates of recidivism. This suggests that, conditional on age, the length of an individual's previous criminal history should be taken into consideration when assigning a socially optimal punishment.

As we will show, there are some areas in which judges (or the laws that they enforce) appear to allocate prison time in an inefficient way, and that crime could be reduced without additional cost if more resources were spent deterring people who, by revealed actions, have a low reservation wage of criminal behavior. We highlight the fact that robbers who work in groups, as well as robbers who use guns and knives are considerably more dangerous that the other robbers. This suggests that sentence enhancements for using any type of weapon in a robbery, rather than a current focus on deterring firearm use, may be warranted. Further, even though the legal system appears to keep robbery "firms" inefficiently small, the punishment for multi-offender robberies do not currently match the criminal return to group offending.

Our chapter is divided into two parts. In the first section, we take a "macro" look at the criminal careers of individuals who, at some point, were incarcerated for robbery in one of two Milanese prisons. Similar to the U.S. Bureau of Justice Statistics "Prisoners Released in 1994" data set, these data not only allow us to describe these "criminal workers" in terms of their gender, educational background, age and ethnicity, but also, using past and future incarcerations, to demonstrate how robbery fits into the career trajectory of these criminals.

Second, we take a "micro" look at individual crimes, using a unique data set collected by the Milan Police Department on all commercial robberies occurring between 2008 and 2010. We observe the time, location, and victim of each event, the amount of loot stolen in euros, the types of weapons used, the estimated age, gender, and nationality of the robbers, and whether or not any of the robbers were arrested. Using detailed victims' reports and video surveillance footage from each of the crimes, the Milan police were able to link robberies committed by the same suspect or suspects. Our ability to study the evolution of crimes committed by the same group of individuals with administrative records is, to the best of our knowledge, an innovation in applied criminal justice research.

It is an unfortunate reality that work done by applied economists outside of the traditional field of economics is often viewed with skepticism by practitioners, especially in Europe. We push back against this, as the application of labor economics to criminal activity is more than an academic exercise. While some of the analysis we present in this chapter is purely descriptive, it does allow us to highlight some potential policy strategies that may improve the efficiency of criminal justice provision in Italy.

This research presented in this chapter is the result of a collaborative effort between academia, police forces (in particular the *Questura di Milano*), and judicial authorities (in particular the Italian prison authority, *Dipartimento di Amministrazione Penitenziaria*). It is our hope that, in the future, these sorts of cooperative research programs become more common. Administrative micro-level data represent an invaluable asset that policy makers and academia should strive to exploit in their fight against crime.

1.1 National and International Comparison of Robberies

This study uses very detailed information about individual criminals and crimes, but we need to keep in mind that the criminals (mostly robbers) and the robberies we study refer to a specific Italian city, namely Milan, the capital of the *Lombardia* region. Before analyzing the Milan data let us devote this section to an international, and national comparison of robbery rates.

Table 1.1 uses data compiled by the United Nations Office on Drugs and Crime to compare the evolution of robbery rates in Italy with robbery rates in 8 other countries. The countries we chose are either neighboring countries (Austria, Croatia, France, Slovenia, and Switzerland), or countries that are of similar size in Europe (Germany and the UK), or countries that have been subject to an extensive research (Canada and the United States). Of course, we need to keep in mind that the legal definition of crimes and accounting methodology used to track criminal incidents varies across countries, making comparisons of trends somewhat more informative than level comparisons.

According to Table 1.1 Italian robbery rates are quite similar to Canadian ones, are lower than French, British, and American rates, and higher than in the remaining 5 countries. Over time, the rates are stable in most countries and decrease substantially in the UK and in the US. Overall Italy tends to have more robberies than neighboring countries (with the exception of France), but less than English speaking countries.

The area under study, which comprises the municipality of Milan (*Comune*) as well as part of the smaller neighboring municipalities around it (*Provincia*) is similar to Philadelphia (Pennsylvania) in terms of population size (roughly 1.34 million people live in the *Comune*, compared to 1.5 million in Philadelphia), and land area (350 square kilometers, or 134 square miles, in both cities).[1].

[1] One can easily compute the land area covered by robberies approximating the such area with a circle,

Table 1.1: Robbery Rates Across Countries

Country	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Austria	-	58.6	57.9	61.6	60.5	57.4	54.7	51.3
Canada	101.5	97.0	100.5	106.2	103.7	97.1	96.4	89.4
Croatia	27.7	36.5	35.1	32.6	28.7	28.5	32.0	28.3
France	208.2	197.4	204.3	207.2	182.8	171.7	180.6	-
Germany	72.5	72.4	66.4	65.1	64.2	60.5	59.8	58.5
Italy	**72.1**	**79.4**	**112.0**	**120.4**	**124.6**	**107.8**	**84.2**	**79.3**
Slovenia	17.5	19.9	21.4	26.2	22.4	19.1	23.8	22.8
Switzerland *	59.4	39.8	53.6	54.7	59.6	55.7	66.0	57.5
United Kingdom (England and Wales)	196.5	171.5	183.8	188.7	156.7	147.1	137.0	137.9
United States of America	142.2	136.5	140.6	150.0	148.0	145.4	132.8	115.3
Italy's ranking	5/9	6/10	7/10	7/10	7/10	7/10	6/10	6/9

Notes: According to the United Nations Office on Drugs and Crime (UNODC) "Robbery" means the theft of property from a person overcoming resistance by force or threat of force. Where possible, the category should include muggings (bag-snatching) and theft with violence, but should exclude pick pocketing and extortion. Rates are per 100,000 inhabitants. Source: United Nations Office on Drugs and Crime http://www.unodc.org/unodc/en/data-and-analysis/statistics/crime.html

Milan is internationally known as one of the most important hubs for the fashion industry, and has one of the highest levels of per capita income in Italy. While high employment and income would tend to be associated with low crime rates, the cost of living in Milan is also quite high. Milan is consistently ranked among the top 20 most expensive cities in world, comparable to cities like Chicago, Sydney, and Paris. Indeed, robbery rates in Milan, as well as trends in those rates, are similar to other cities with more than 300,000 inhabitants, both within Italy and internationally.

Figure 1.1 shows the evolution of robberies in 11 Italian cities over the last 20 years, divided by region (north, center, and south). With the exception of cities in Sicily (Palermo and Catania), robbery rates have grown steadily over time. Between 1984 and 2006 robberies rates in Milan more than doubled from about 110 per 100,000 inhabitants to about 300. This is very consistent with trends in other large northern cities. Robbery rates in cities that are located in Central Italy tend to be lower, but they also rise over this time period at a similar rate.

and using the fact that the radius is between 10 and 11 km (7 miles).

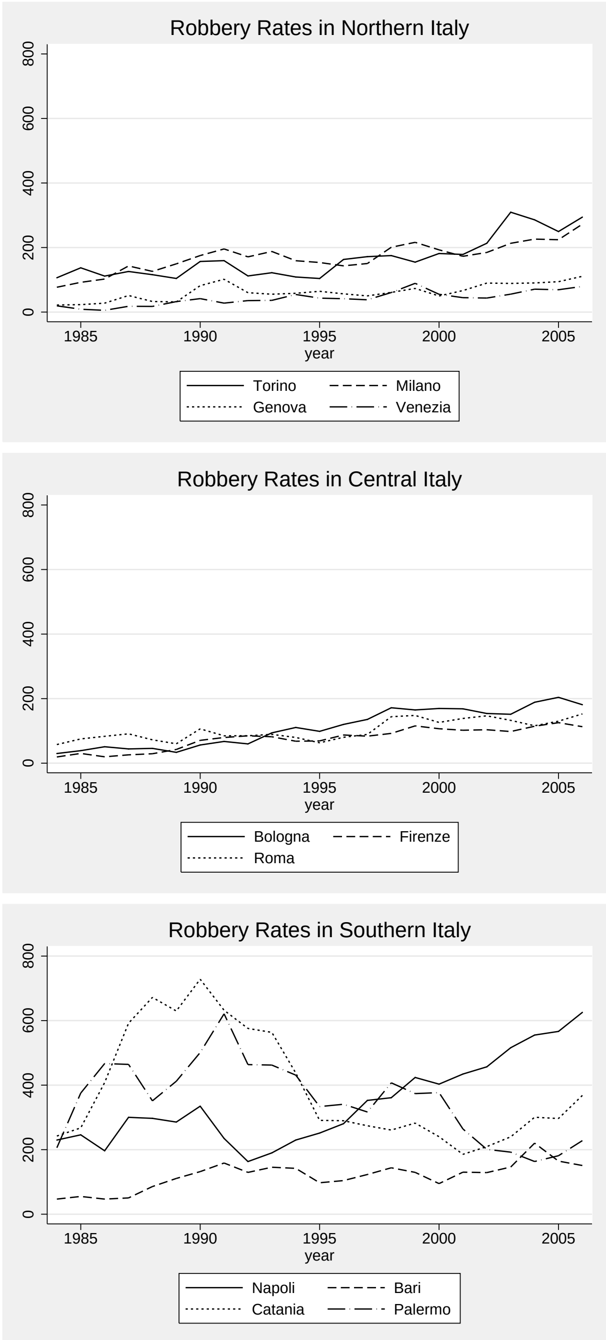

Figure 1.1: Robbery Rates Across Major Italian Cities

Notes: The rates are per 100,000 inhabitants and based on Police Data.

One frequently cited explanation for this slow, steady rise in crimes in the northern and central regions is migration of criminals from the south. Indeed, 43 percent of prisoners in Milan were born in the southern regions of Basilicata, Calabria, Campania, Molise, Puglia and Sicilia.

Cities in the south of Italy have similar crime rates at the beginning of the sample, but these rates quickly diverge. In Palermo and Catania, robberies peaked around 1990, and later declined quite dramatically. Crime trends in Bari, the main city in the region Apulia, are more similar to the those of northern cities. Naples, on the other hand, has the most astonishing increase in robberies. Over 20 years its rates tripled from 200 to more than 600. By the end of the period Neapolitan robbery rates are more than twice as large as robbery rates in all the other cities.

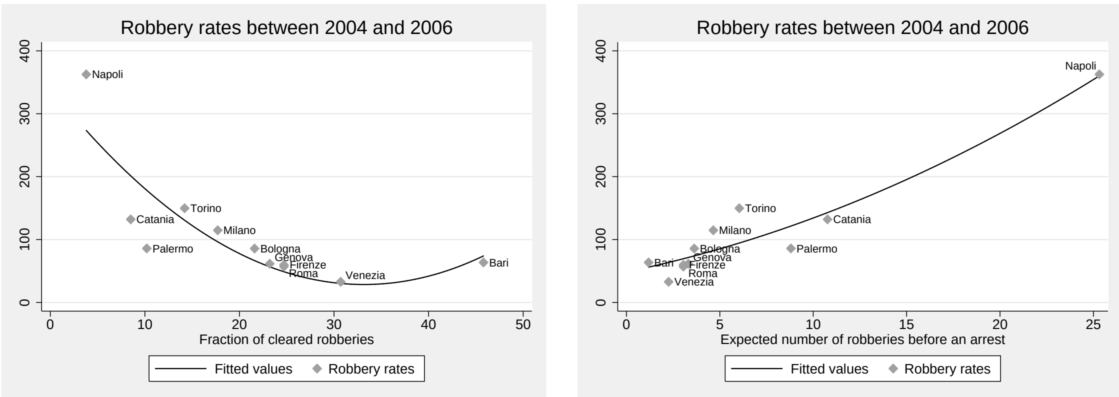

Figure 1.2: Robbery Rates and Clearance Rates

Notes: The street robbery rates are per 100,000 inhabitants and based on Police Data. Clearance rates are defined as the fraction of robberies for which perpetrators have been identified.

Figure 1.2 shows that, to some extent, these regional differences are a function of the local policy environment. According to police statistics, only 3.8 percent of street robberies are cleared in Naples, while the city with the second highest crime rate, Catania, has a clearance rate of 8.5 percent.[2] Plotting the robbery rates against the clearance rate reveals a strong negative relationship, which could be due to varying levels of deterrence, incapacitation, or both. Some basic regression diagnostics implies that a negative exponential regression fits the data well, which is consistent with an incapacitation effect.

[2]The Police only publish clearance rates for street robberies, which represent about 40 percent of all robberies.

By imposing some structure on the data, we can further explore the relationship between crime and clearance rates. If we assume i) a constant clearance rate p, ii) that robbers can potentially rob a very large number of victims T, and iii) that criminals persist in robbing victims until arrested, the expected number of robberies for any given team of robbers is defined as:

$$E(R) = \sum_{t=0}^{T}(1-p)^t = \frac{1-(1-p)^T}{p} \approx \frac{1}{p}$$

Using the expected number of robberies, as opposed to the clearance rate, as a regressor (right panel), the relationship with the robbery rate is indeed almost linear, and instead of being an anomaly, the high robbery rate in Naples can be almost completely explained by the reduced levels of incapacitation in that city.

Of course, given the simplifying assumptions and the non-perfect linear relationship, the evidence is not a sufficient test to exclude the possibility that deterrence is in part responsible for the negative relationship between robberies and clearance rates (see also Mastrobuoni (2012)). However, it is suggestive that the perceived expected probability of punishment conditional on arrest is relatively constant across Italy.

Conditional on the clearance rate, people in Milan appear to have roughly similar propensities to commit robbery as the residents of other major Italian cities. Of course, Italy is not just made up of cities, and there is a large amount of mobility between the more rural areas and the central urban districts.

In Figure 1.3, we compare regional crime rates in the *Lombardia* region to other Italian regions. Not surprisingly, regional robbery rates are about two times smaller than the robbery rates in the corresponding cities. Since regional statistics include larger cities, robbery rates in smaller cities, as well as in the countryside are likely to be even lower.

The rates in *Lombardia* evolve in a way that is very similar to the second major region in the north, *Piemonte*. The remaining regions don't have major cities, which is probably

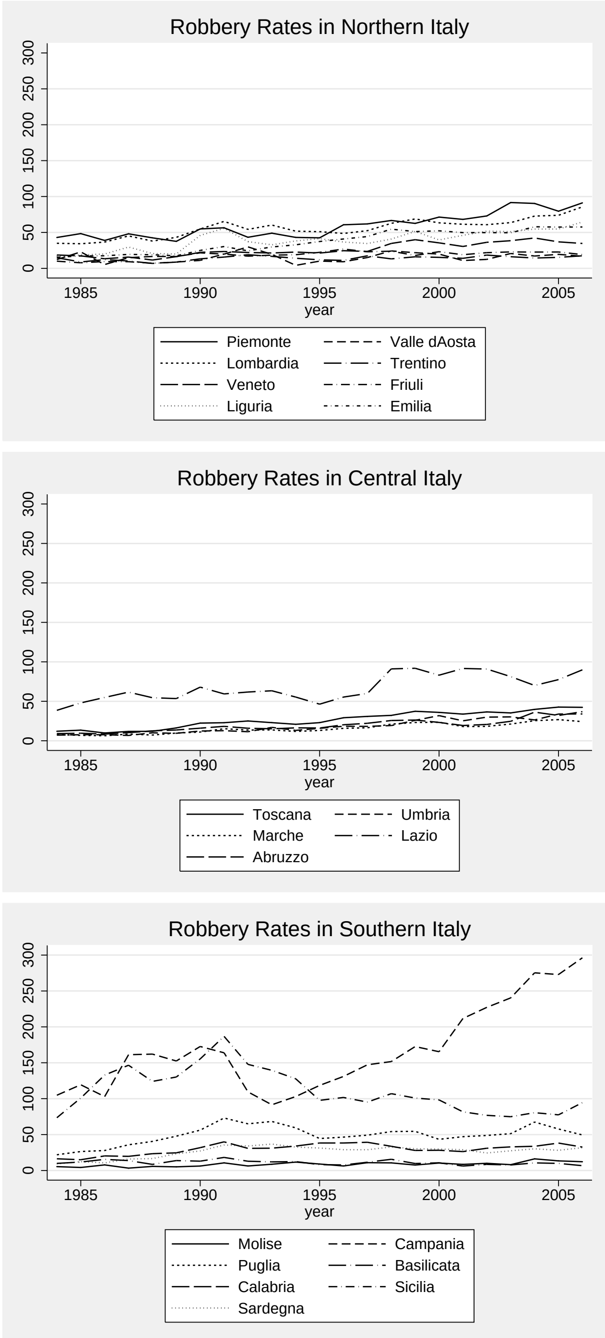

Figure 1.3: Robbery Rates Across Italian Regions

Notes: The rates are per 100,000 inhabitants and based on Police Data.

why the corresponding robbery rates are smaller. In the center of Italy, Lazio has similar rates as *Lombardia*, and also exhibits a similar time trend, while the remaining regional rates are considerably smaller. The south, again, shows considerable heterogeneity. Crime rates in Campania are about 3 times larger than any other region. Sicily has a high crime rate, and is the only region with a decreasing trend in robberies over time.

Summing up, Italian robbery rates compare well to robbery rates in English speaking countries. Robbery rates in Milan, and in the *Lombardia* region more generally, are quite typical for Italian cities and regions. For the most part, variation in robbery rates across cities appears to be driven by variation in arrest rates (incapacitation), rather than regional differences in criminal propensity.

Chapter 2

The Criminal Careers

Based on unemployment insurance records in the United States, in any given year, one out of every 10 of workers leave their jobs, and are re-hired in a different industry (Golan et al., 2007). Similarly, it is not unusual to see illegal workers switch industries over time, in the sense that someone incarcerated for robbery in 2001 may very well be incarcerated for burglary in 2006. In most developed countries workers leave the labor market between the age of 60 and 65, depending on their wages, their retirement benefits, and their savings. Criminals' decision to "retire" is likely to depend on different factors.

The frequency with which criminals transition from one type of crime to another, and their decision to quit means that, in order to properly interpret our description of a successful and productive robbery organization, it is important to consider how robbery fits into a typical career path. We therefore begin our analysis of criminal workers and criminal firms by describing how robbery fits into the typical career of a Milanese criminal.

2.1 The Prison Data

An important source of information that has traditionally been used to study criminal behavior comes from prison records. We were given access to prison records of inmates who between January 2001 and October 2012 were incarcerated in one of two Milan prisons, Bollate and Opera. According to Italian law, all arrested individuals are initially held in the judicial jurisdiction where the alleged crime occurred (Barbarino and Mastrobuoni, forthcoming). As a result, while confidentiality concerns prohibit us from linking prison data to the data on criminal firms that we are going to employ in Section 3, we can be confident that the individuals in our prison data are tightly linked to the individuals working in the illegal firms tracked by the Milan police.

At our request, prison administration employees reconstructed the past incarceration history of all inmates who were incarcerated at least once in the Bollate or Opera prisons. We further refined the sample to people who, at some point in their criminal careers, were convicted of robbery. As such, our prison data allow us to view the entire criminal careers of people who might operate in many different "illegal industries" over the course of their working life. Table 2.1 contains descriptive statistics of these workers at each point of incarceration. The roughly 7,000 robbers in our sample were incarcerated an average of 4.4 times each, and we observe a total of almost 30,000 unique incarceration spells.

The inmates in our sample are almost all male. About 2/3 are single, 24 percent are in a relationship, and 5.5 percent are separated or divorced (the rest are widowed). The average age they entered prison for the first time is 25, and people are, on average, 33 when they are released. For each person in our sample, we will define the age of their first incarceration as their "entry" into the criminal labor market, even though this is obviously a lower-bound of their unobserved experience as criminals. Even with this lower bound, we are still able to observe long careers; one individual has been in and out of prison for 41 years.

The average duration of an incarceration (a few are right truncated, meaning that the inmates are still behind bars) is 1.4 years. The longest time spent in jail in one incarceration spell is 37 years. The average number of individual incarcerations is 4.4, though one criminal has been in jail a staggering 29 times.

Table 2.1: Characteristics of Robbers

Variable	Mean	Std. Dev.	Min.	Max.	N
Male	0.992	0.091	0	1	29662
Single	0.631	0.483	0	1	29662
In a relationship	0.239	0.426	0	1	29662
Separated or divorced	0.055	0.228	0	1	29662
Age	33.227	10.029	14	83	29662
Age at first incarceration	25.159	7.336	14	83	29662
Experience	8.068	7.024	0	41	29662
Incarceration length (years)	1.421	2.337	0	37.37	24031
Total number of incarcerations	4.376	3.689	1	29	29662
College degree	0.047	0.211	0	1	29662
Secondary schooling	0.439	0.496	0	1	29662
Primary schooling degree	0.23	0.421	0	1	29662
Schooling Unknown	0.257	0.437	0	1	29662
Employed	0.143	0.351	0	1	29662
Unemployed	0.18	0.384	0	1	29662
Employment unknown	0.642	0.479	0	1	29662
Homicide	0.051	0.22	0	1	29662
Assault	0.172	0.377	0	1	29662
Sex-related crime	0.016	0.126	0	1	29662
Theft	0.378	0.485	0	1	29662
Robbery	0.388	0.487	0	1	29662
Extortion	0.064	0.244	0	1	29662
Possession of stolen goods	0.172	0.377	0	1	29662
Drug-related crime	0.176	0.381	0	1	29662
Other crime	0.31	0.462	0	1	29662
Persistence across crimes	0.584	0.493	0	1	23350

A few criminals (4.7 percent) have a college degree, while most have secondary (44 percent) or a primary (23 percent) schooling degree (by comparison, in Italy as a whole from 2009 to 2011, an average of 20.6 percent of the population had a college degree, while 32 percent had a secondary schooling degree and only 3 percent stopped with a primary schooling.[1]) For a quarter of our sample this information is not available. But these aggregate numbers mask changes across year of birth cohorts. Figures 2.1 and 2.2 show the evolution of educational degrees for Italian and foreign inmates across the different years of birth. Among Italians, more and more inmates are drawn from the middle of the educational distribution, while fewer and fewer inmates have no schooling or just a primary schooling degree. This tracks the trend in the general population. The evolution of the fraction of inmates with at least a high school degree is more interesting, as it moves against the increasing trend for the overall population, where the fraction moved from 63 percent to 71 percent over the period 2004 to 2011. [2] This is likely to reflect an increasing opportunity cost of criminal behavior for those who have enough schooling.

For foreign inmates, the trends for high school graduates is very similar in both levels and changes. The fraction of inmates with no schooling, or just primary schooling, instead, are considerably larger, and show little change over time. This seems to suggest that the educational composition of inmates that are not Italian is changing much less than the one of Italian inmates.

Compared to information on educational attainment, we observe very little detail about the legal work history of the people in our sample. Employment status is unknown for almost 2/3 of inmates. The remaining third is almost evenly split between employment and unemployment.

Figure 2.3 shows that inmates of all ages have missing employment information. Among those for which we have employment data, the employment rate does appear

[1] Source: I.Stat.
[2] Source: I.Stat.

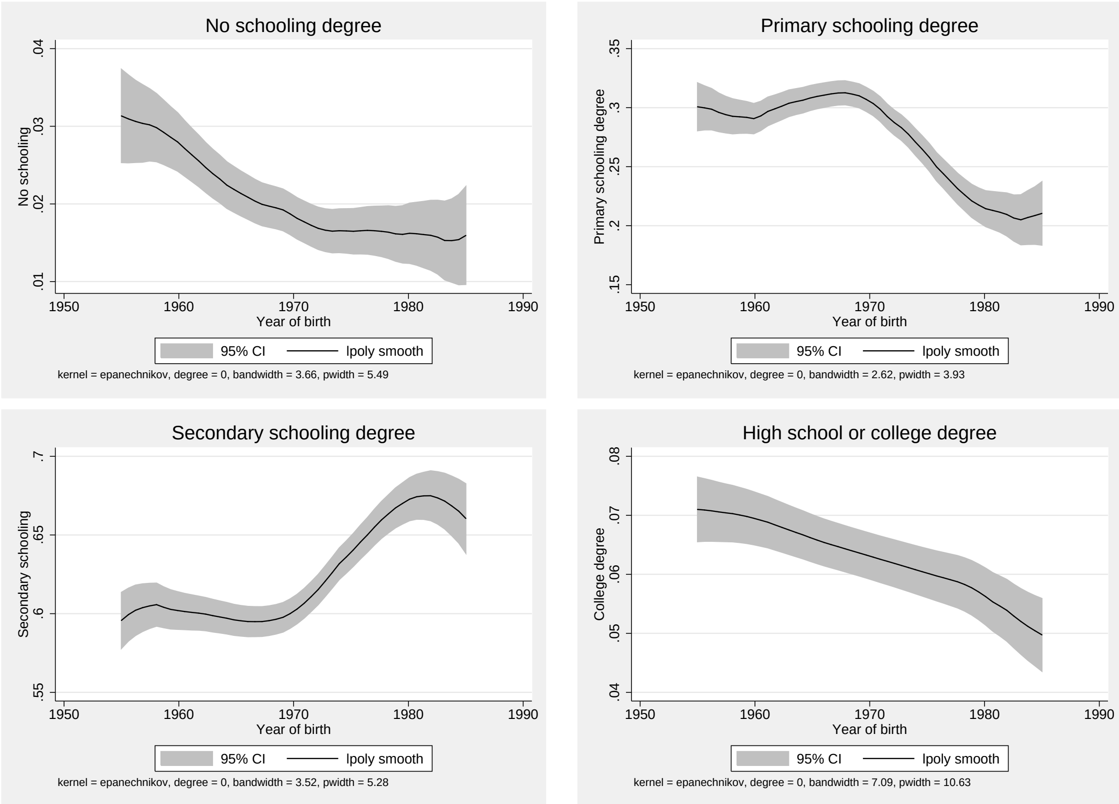

Figure 2.1: Schooling and the Year of Birth for Italian Inmates

Notes: Figures based on kernel-weighted local polynomial regression. When calculating the fraction of inmates with a secondary or a high school degree inmates are at least 15 and 20 years old. The grey areas represent the 95 percent confidence intervals.

to be related to age; while only 20 to 30 percent of inmates appear to employed when they are 18 to 20 years old, such fractions increase rapidly over age and peak between 45 and 55, much like for the overall population (though the peak employment rates for Italy as a whole are reached earlier in life, between the ages of 35 and 44 [3]).

Unemployment rates are very high when inmates are young (less than half of the inmates looking for a job can find one when they are around 20), and are considerable even at more advanced ages (20 to 30 percent).

For each incarceration spell, the prison records contain information on all crimes for which an inmate was convicted. Since criminals might be incarcerated for more than one crime the percentages sum up to more than one. The most common crimes are

[3] Source: I.Stat.

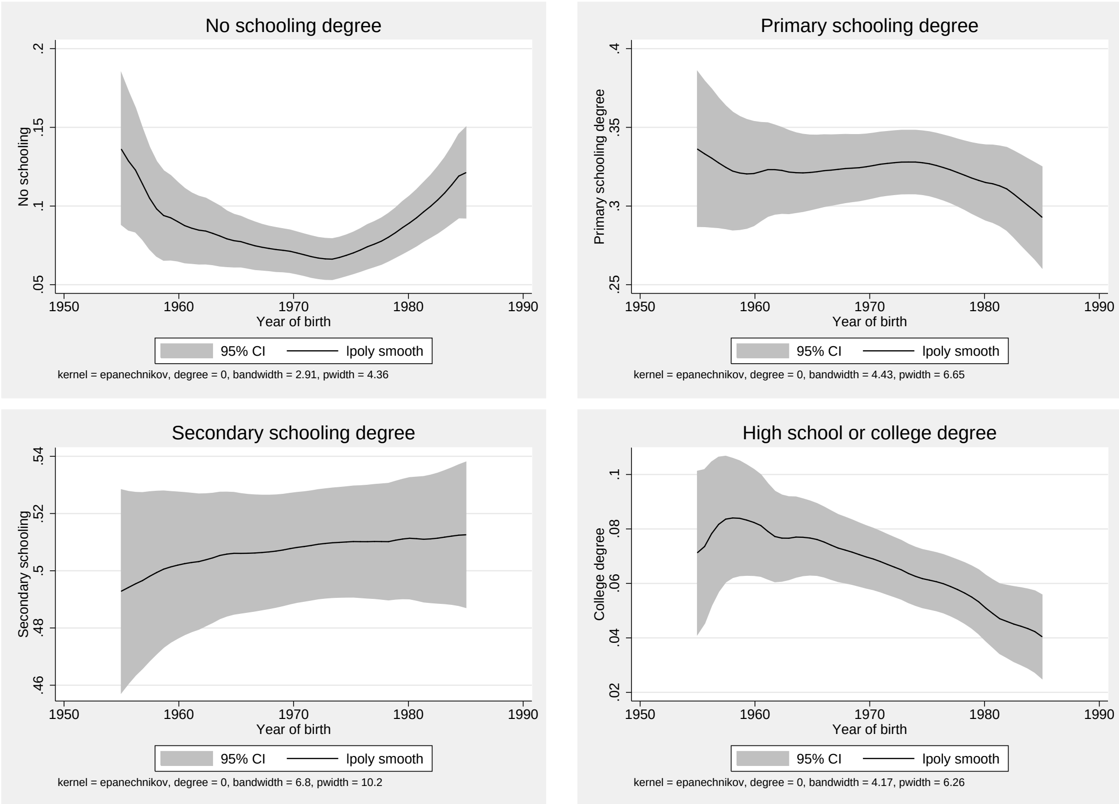

Figure 2.2: Schooling and the Year of Birth for Foreign Inmates

Notes: Figures based on kernel-weighted local polynomial regression. When calculating the fraction of inmates with a secondary or a high school degree inmates are at least 15 and 20 years old. The grey areas represent the 95 percent confidence intervals.

robberies (39 percent of incarceration), which is not surprising given that we sampled only criminals with at least one robbery in their criminal history. Together with the thefts (38 percent), drug-related crimes (17.6 percent), and possession of stolen goods (17 percent) these crimes make up the grand majority of convictions. Assaults are quite common (17 percent), while homicides are less common (5 percent). The residual category "other crimes" covers 31 percent of the incarcerations.

The inmates come from 74 different countries. Table 2.2 shows the 10 main countries of citizenship of inmates, representing 90 percent of the prison population in our sample. The distribution is split in pre 2008 and post 2008 incarcerations, and to highlight differences over time the last column computes the relative changes over time. Overall,

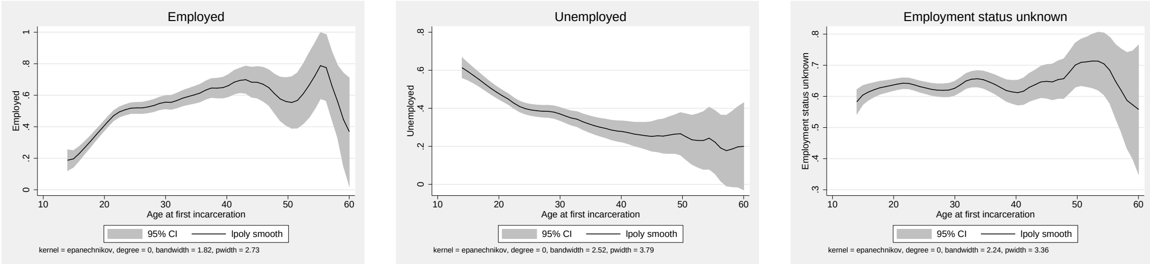

Figure 2.3: Employment Status and the Age at First Incarceration

Notes: Figures based on kernel-weighted local polynomial regression. 95 percent confidence intervals.

85 percent of inmates are Italian, a fraction that decreased a little in more recent years. By comparison, the fraction of foreigners in Italy also increased, but from 4 percent to 7 percent (comparing pre- and post-2008). In Milan foreigners represent a larger and also growing fraction of the population, compared to Italy as a whole: before 2008, 11 percent of Milanese residents were foreign, increasing to 15 percent in the post-2008 period. [4] The two largest non-Italian prison communities are Algerians and Moroccans, though in more recent years the population of Romanians and Albanians has grown relatively rapidly (Mastrobuoni and Pinotti, 2012). This demographic shift is apparent in national census data as well: for Italy as a whole, the two largest non-Italian communities are Albanians and Moroccans pre-2008 (0.67 and 0.62 percent of the total population, respectively), and Albanians and Romanians after 2008 (0.77 and 1.47 percent, respectively). However, in both periods for Milan the largest country of origin for foreigners is the Philippines (its share of the total population increases from 1.8 to 2.4 percent), followed by Egypt (whose share increases from 1.4 to 1.99 percent) and China (whose share increases from 0.9 to 1.3 percent), all of which are clearly under-represented in jail.[5]

Table 2.3 shows that most Italian robbers who end up being jailed in Bollate and Opera are natives of *Lombardia*. The second most represented region of birth is Sicily, followed by Campania and Puglia. Compare this to *Lombardia* as a whole, where after

[4] Source: I.Stat.
[5] Source: I.Stat.

Table 2.2: Nationalities of Robbers

	Pre 2008	Post 2008	%Δ
Algeria	3.5%	1.73%	-0.500
Albania	0.7%	1.62%	1.478
France	0.5%	0.44%	-0.051
Italy	85.8%	81.94%	-0.045
Germany	0.2%	0.26%	0.168
Morocco	3.9%	5.17%	0.328
Peru	0.5%	0.27%	-0.454
Romania	0.6%	2.15%	2.381
Tunisia	0.8%	0.97%	0.268
Yugoslavia (Former)	1.0%	0.56%	-0.432
N.obs.	22,675	6,987	

Lombardy (40 percent) the most represented region of birth is again Sicily (7.4 percent), followed by Piedmont and Emilia-Romagna (6.45 and 6.40 percent, respectively)[6].

According to Italian law, criminals are incarcerated in a region either because they reside in that region, or because they committed a crime in that region. Information on both the region of birth and region of residence allows us to have a crude measure of the fraction of criminals who "commute" or have recently migrated to *Lombardia* to run their illegal activities.

Overall only 28 percent of inmates do not reside in the region where the jails are located. Inmates who were born in regions that are close to *Lombardia* are less likely to reside in *Lombardia* than inmates who were born in regions that are far away, though there are a few exceptions, Lazio (88 percent of commuters), *Umbria* (85.5 percent), *Abruzzo* (59 percent), and *Campania* (53 percent). Despite being a several hour drive away from *Lombardia*, these criminals appear to be commuting to the richest Italian region to organize their illegal business.

Another way to see this, is by correlating a region's robbery rate (number of robberies per 100,000 population) with the share of prisoners born in that region. Such correlation

[6]Source: Italian municipal data.

is equal to 0.58 (see Figure 2.4) and can be interpreted as implying an "exporting" of criminals from regions with high crime rates to Milan, where they commit crimes and are arrested.[7]

Table 2.3: Regions of Birth of Italian Robbers in Milan

	Regions of birth (in percent)			
	Overall	Resident in Lombardia		Ratio of commuters
		Yes	No	
Abruzzo	0.4	0.2	0.8	59.2%
Basilicata	0.9	0.8	0.9	31.2%
Calabria	6.6	6.3	7.5	32.4%
Campania	12.8	8.4	23.7	53.0%
Emilia Romagna	1.8	0.7	4.4	70.8%
Friuli Venezia Giulia	0.5	0.2	1.4	77.6%
Lazio	2.2	0.4	6.8	88.0%
Liguria	1.4	0.9	2.6	53.4%
Lombardia	42.7	56.4	8.4	5.7%
Marche	0.1	0.1	0.1	39.1%
Molise	0.1	0.1	0.0	0.0%
Piemonte	2.2	1.2	4.7	60.6%
Puglia	9.3	9.4	9.3	28.5%
Sardegna	1.9	1.7	2.4	36.4%
Sicilia	13.6	12.0	17.6	37.0%
Toscana	0.5	0.2	1.4	72.2%
Trentino Alto Adige	0.3	0.1	0.9	80.2%
Umbria	0.1	0.0	0.4	85.5%
Veneto	2.6	0.9	6.7	74.3%
Total	24,875	17,758	7,117	28.6%

[7]Source: I.Stat.

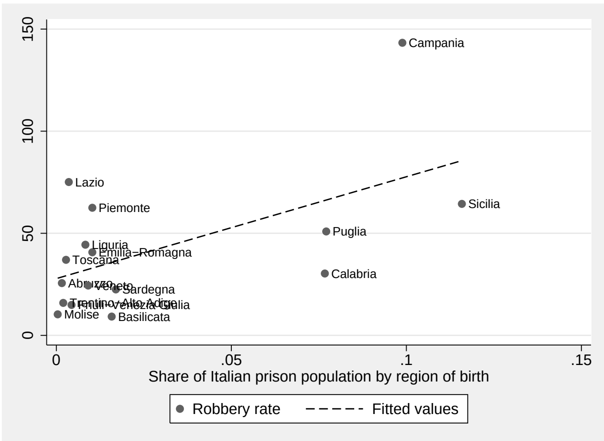

Figure 2.4: Region of Birth and Regional Robbery Rates

Notes: The figure plots regional robbery rates against the share of Milan prison population from the same region. The linear fit is based on a simple OLS regression.

2.2 Non-Parametric Analysis of Career Paths

In this section we use our prions data to describe the evolution of criminal behavior over time (age and experience), both at the extensive (whether to commit crime or not) and the intensive margin (how frequently to commit crime).

Figure 2.5 shows the well-known fact that there is a negative age gradient in recidivism- almost 90 percent of younger criminals are re-incarcerated at some point, compared to less than 60 percent of inmates incarcerated in their 60s. As pointed out in Blumstein et al. (1986), this observed decline could be driven by either a change in the frequency with which the same set of older criminals commit crimes, or a change in the composition of criminals due to exit from the criminal labor market, through either mortality or a behavioral change.

We are able to partially disentangle a change in criminal frequency from true desistance by comparing the time it takes for criminals of different ages to recidivate. The right panel of Figure 2.5 shows that the number of days in between subsequent incarcerations gets shorter and shorter as criminals age. Around age 20 criminals are back in jail after about 700 days, 5 years later after 550, where it levels off, suggesting that, if anything, older criminals offend at a higher frequency than younger criminals. This suggests that people who are still engaging in crime at 50 are, by this measure, more criminal than younger offenders. Marginal criminals appear to select out of the crime market as they age.

Of course, this pattern might also in part be based on a different type of selection- if the police can more easily find evidence necessary to convict offenders who they have become familiar with.

We now turn to when people enter those potentially lengthy criminal careers. The distribution of the age at which criminals enter jail for the first time, which again is an upper-bound for the age at which they start their criminal career, spikes at age 20 and is highly concentrated (Figure 3.4). The majority of inmates enter jail for the first

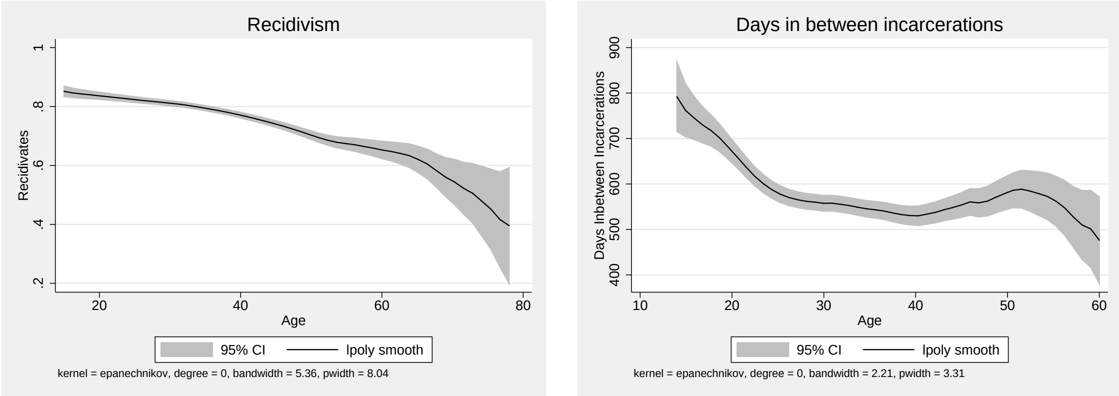

Figure 2.5: Likelihood of Recidivism on Age and of the Days In Between Incarcerations

Notes: Kernel-weighted local polynomial smoothing. The shaded area represents the 95 percent confidence interval.

time prior to turning 30. The distribution of age at which inmates are observed during their last incarceration, a lower-bound for the age of retirement from their criminal job is considerably more widespread, and peaks around 40 years old.

Recall that we define a criminal's experience as the time since their first incarceration. Table 2.1 showed that such variable has an overall mean of 8 years. When we condition the sample on people in their last observed incarceration spell, average experience is about 13 years. We will use our measure of experience to characterize criminal workers at the beginning and end of their careers.

Table 2.4 splits the data into experience quartiles and crime types, showing both the total number of observations and the frequency row-normalized to sum to one (in parentheses). In other words, the frequencies measure the likelihood of a given crime type to fall into one experience quartile. Workers at all experience levels appear to commit robbery, although there a slight increase in robbery in the highest quartile of experience.

The largest deviations from 25 percent are at lower quartiles. This means that at the beginning of their career, criminals are more likely to be involved in thefts and in drug-related crimes, and less likely to be involved in sexual crime, homicides, and assaults.

Assaults are most likely to happen in the middle of one's criminal career, while homi-

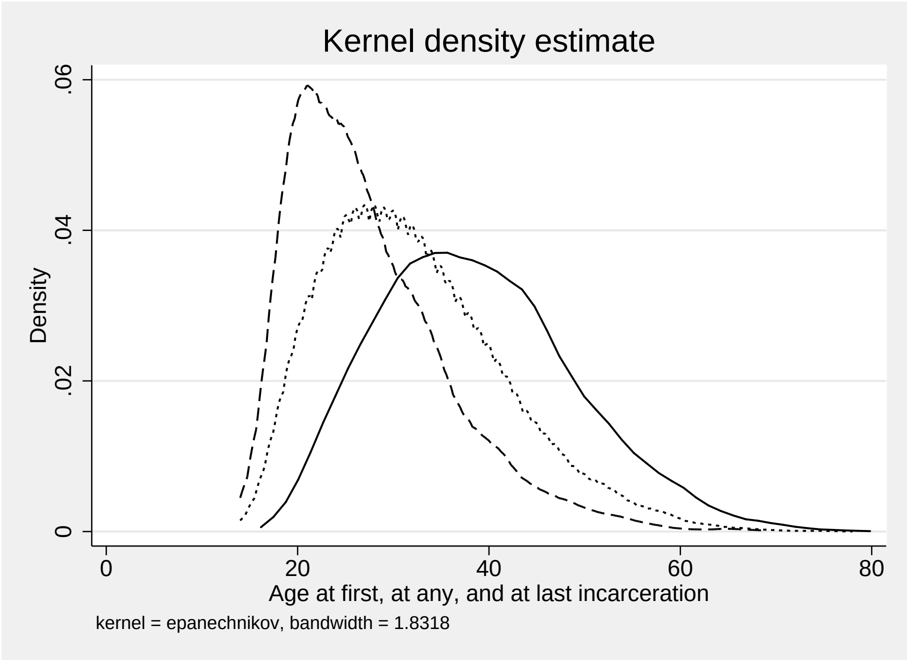

Figure 2.6: Densities of Age in Prison Data

Notes: The age variables for the prison administration are based on the first observed age at entry (dashed line), at the current age (dotted line), and the last observed age at incarceration (solid line).

cides tend to end someone's career, in part because of longer prison times. Petty crimes are less likely at the upper quartile of the experience distribution, showing that criminals tend to commit more and more serious crimes as they age within their criminal career.

Table 2.4 suggests that criminals may engage in robbery at any point in their criminal life. Another way to think about the role of robbery work in a criminal career is to look at the first "jobs" that robbers have. Figure 2.7 shows, for each age, the fraction of first time criminals who commit a given offense.

In the central panel, the fraction of first-time offenders who commit robbery is increasing in age, which is essentially mechanical; this is a sample of robbers, and so as people get older and older and increasing fraction of them must enter the criminal market as robbers. However, only 60 percent of robbers who begin their careers at 45 to 50 years old enter the market as robbers, implying that even at that advanced age, almost half of eventual robbers enter the illegal industry through another criminal path. It is also notable that

Table 2.4: Crime Types by Experience Quartiles

	Experience quartiles				
	1st	2nd	3rd	4th	Total
Assault	144	205	228	183	760
	(18.95)	(26.97)	(30.00)	(24.08)	(100.00)
Drug-related crime	396	354	293	295	1,338
	(29.60)	(26.46)	(21.90)	(22.05)	(100.00)
Extortion	58	82	72	60	272
	(21.32)	(30.15)	(26.47)	(22.06)	(100.00)
Homicide	182	211	290	579	1,262
	(14.42)	(16.72)	(22.98)	(45.88)	(100.00)
Other crime	494	493	524	383	1,894
	(26.08)	(26.03)	(27.67)	(20.22)	(100.00)
Possession of stolen	258	320	281	270	1,129
	(22.85)	(28.34)	(24.89)	(23.91)	(100.00)
Robbery	1,562	1,404	1,567	1,668	6,201
	(25.19)	(22.64)	(25.27)	(26.90)	(100.00)
Sex-related crime	5	11	11	15	42
	(11.90)	(26.19)	(26.19)	(35.71)	(100.00)
Theft	953	972	786	600	3,311
	(28.78)	(29.36)	(23.74)	(18.12)	(100.00)
Total	4,052	4,052	4,052	4,053	16,209
	(25.00)	(25.00)	(25.00)	(25.00)	(100.00)

Notes: The average experience for 1st to the 4th quartile of experience is 7, 10, 14, and 21 years.

younger robbers are more likely to begin their careers as thieves, drug offenders, or other types of petty criminals. Older robbers, on the other hand, are more likely to first be incarcerated for violent or more sophisticated property crimes like extortion or possession of stolen goods.

Once people have entered the criminal market, we can use the controlling offense of all subsequent incarcerations to track how workers move between industries. Table 2.5 presents the estimated transition matrix between different criminal industries. We computed two matrices, based on whether the criminal's experience is above or below the median in our sample. The last column shows the steady state distribution of crimes, again by experience level.

Industry switching is, for the most part, more common in the illegal sector than in the legal one; roughly one in five of men between 18 and 25 switch careers each year (Golan et al., 2007), meaning that at most 74 percent will switch over the course of

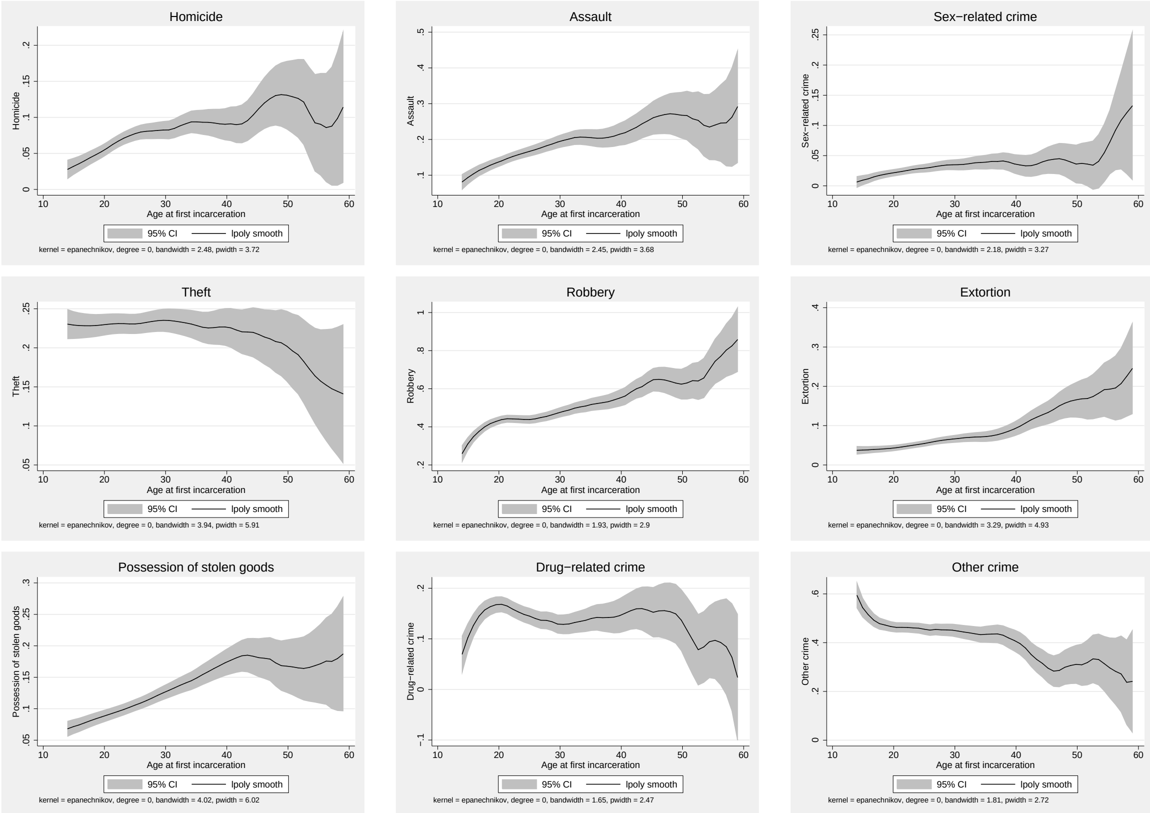

Figure 2.7: Crimes and the Age at First Incarceration

Notes: Kernel-weighted local polynomial smoothing. The shaded area represents the 95 percent confidence interval.

six years. Amongst the inexperienced criminals, drug offenders, thieves, and non-index offenders are more persistent in their industry choice than legal workers, and robbers are roughly as persistent.

Notably, and in contrast to the legal sector, it is not obviously the case that criminals with more experience are much less likely to change careers over time. For example, 25 percent of robbers in both experience groups, when they are reincarcerated, are reincarcerated for robbery. This is only a slightly higher transition probability than people who enter the prison system for other crimes. Theft is the more "absorbing" of all offenses, with 46 percent of new thieves and 35 of experienced thieves staying in the theft industry for at least one more period, and almost a quarter of inexperienced robbers are reincarcerated for theft. The persistence of theft among robbers implies that robbery is a rare compliment to a thief's career, rather than a natural progression of escalating criminality.

The most striking difference across experienced and inexperienced criminals is the timing of other "non-index" offenses. While 13 percent of experienced criminals will commit these types of crimes in the steady state, inexperienced offenders who commit a non-index offense have a 41 percent chance of entering the robbery industry in the next period- more than twice the switching rate of their experienced colleagues. Notice also that more experienced criminals are more likely to engage in persistent robbery; the observed transitions from re-incarcerated criminals suggests that there will be 10 percent more "experienced" robbers in steady state.

In general, once workers participate in robbery, they seem to transition away from violent and non-income generating offenses; very few inexperienced or experienced workers transition into homicide, extortion, or sexual assault. In contrast, the transition matrices suggest that robbery is rarely the first offense a criminal commits. In other words, among inexperienced criminals, all violent offenders are approximately equally likely to become robbers in the next period. Amongst experienced criminals, transitioning to robbery is equally plausible for almost all crime types, although most likely for robbers. This suggests that, from a policy perspective, established robbers are only slightly more likely to commit robbery in the future than other types of criminals, and that robbery is, in some ways, an experienced criminal's game.

Finally, in figure 2.8, we provide further evidence on specialization in the criminal labor market, by plotting probability that a criminal is reincarcerated for the same offense, by years of experience. This is essentially the diagonal elements of a year-by-year version of table 2.5. In the left panel, when we look at all crimes, we see a decline in specialization for the first five years of a criminal's career. In the context of our data, this means that during the five years after an individual's first period of incarceration, they are increasingly likely to become robbers, rather than something else. After 5 years, however, the probability that criminals stay in the same industry begins to rise, eventually reaching roughly 68

Table 2.5: Transition Matrix Across Crime Sectors

	Panel A: Below median experience (≤ 6 years)									
$t \setminus t-1$	Rob.	Hom.	Ass.	Sex.	The.	Ext.	Poss.	Dru.	Oth.	Steady state
Robbery	0.25	0.26	0.24	0.25	0.19	0.22	0.22	0.18	0.17	0.20
Homicide	0.01	0.12	0.02	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Assault	0.11	0.08	0.17	0.13	0.08	0.11	0.09	0.08	0.06	0.09
Sex related c.	0.01	0.00	0.02	0.15	0.00	0.01	0.01	0.00	0.00	0.01
Theft	0.24	0.17	0.19	0.15	0.46	0.17	0.25	0.18	0.18	0.27
Extortion	0.03	0.06	0.03	0.06	0.02	0.16	0.03	0.02	0.02	0.03
Poss. stolen g.	0.07	0.03	0.07	0.03	0.06	0.08	0.16	0.05	0.05	0.07
Drug rel. c.	0.10	0.07	0.08	0.06	0.05	0.08	0.07	0.29	0.10	0.10
Other c.	0.19	0.21	0.19	0.18	0.14	0.16	0.17	0.19	0.41	0.22
	Panel B: Above median experience (> 6 years)									
$t \setminus t-1$	Rob.	Hom.	Ass.	Sex.	The.	Ext.	Poss.	Dru.	Oth.	Steady state
Robbery	0.25	0.23	0.23	0.19	0.20	0.21	0.22	0.20	0.23	0.22
Homicide	0.03	0.14	0.03	0.02	0.02	0.07	0.03	0.03	0.02	0.03
Assault	0.12	0.12	0.17	0.17	0.09	0.13	0.11	0.09	0.10	0.11
Sex related c.	0.01	0.00	0.01	0.15	0.01	0.01	0.00	0.01	0.01	0.01
Theft	0.20	0.11	0.20	0.17	0.35	0.13	0.22	0.16	0.21	0.23
Extortion	0.04	0.07	0.04	0.03	0.02	0.16	0.04	0.04	0.04	0.04
Poss. stolen g.	0.14	0.13	0.12	0.06	0.13	0.11	0.19	0.11	0.12	0.13
Drug rel. c.	0.09	0.09	0.07	0.10	0.07	0.08	0.08	0.23	0.09	0.09
Other c.	0.13	0.11	0.12	0.11	0.11	0.11	0.11	0.12	0.18	0.13

percent after 20 years of experience.

This is consistent with a sorting model of criminal behavior, where individuals initially may not have clear signals about the work they are best suited for. Over time, however, workers learn their type, and are sorted into the best industry for them. This sorting model seems particularly strong for robbery, in the right panel. With every year of experience, robbers are increasingly more likely to stay in the robbery industry, and workers with more than 20 years of experience have a less than 20 percent chance of switching.

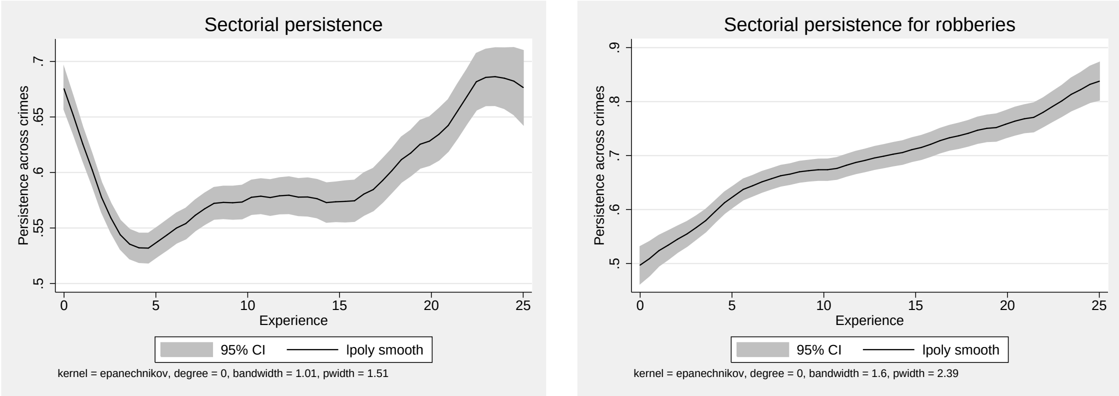

Figure 2.8: Persistence in Crime

Notes: Figures based on kernel-weighted local polynomial regression. 95 percent confidence intervals.

2.3 The End of a Career: A Parametric Analysis of Recidivism

In the previous sections we have shown that criminals rate of recidivism decreases with age, though with considerable heterogeneity across criminals. Such heterogeneity generates a distribution of "retirement ages" that is far less concentrated when compared to the distribution of "initiation ages," the ages at which criminals enter jail for the first time.

While early interventions like the Head Start program have shown to reduce the propensity to develop a criminal career (Garces et al., 2002), the heterogeneity in retirement ages might contain information about what works to reduce recidivism. This section is going to focus on what drives recidivism, or by symmetry, what determines the decision to a abandon a criminal career.

This study is clearly not the first to model recidivism. Gendreau et al. (1996) present a meta-analysis of 131 independent studies, showing that someone's criminal history helps predicting recidivism. Nagin et al. (2009), who review the large literature on the effect of imprisonment on later recidivism, conclude that "(c)ompared with noncustodial sanctions, incarceration appears to have a null or mildly criminogenic effect on future criminal behavior."

The possibility that incarceration not only generates specific deterrence but might also have a criminogenic effect is likely to explain why so many non-experimental studies fail to find evidence of a deterrent effect from criminal sanctions.[8]

Such effect may be contingent on prior experience with imprisonment, stage of criminal career development, and age. Also, imprisonment is selectively imposed. Persons who are sentenced to prison are likely to be less sensitive to deterrence, and such selection is likely to be increasing in the number of incarcerations. These differences must be accounted for to isolate the effect of imprisonment on subsequent criminal behavior.

While we do not have quasi-experimental variation in sentence length, our dataset does contain unusually detailed information on the inmates' criminal careers, allowing us to minimize, although not eliminate, selection on unobserved factors. We will use this detailed data to highlight characteristics and sentencing decisions that are associated with lower rates of recidivism. Our emphasis will be on how the relationship between demographic characteristics and policy choices, like sentence length, and recidivism can change over the course of a criminal career.

While we have information on each criminal's entire criminal history, recall that our sample is based on people who were incarcerated in Bollate or Opera prisons at some point between 2001 and 2012. Therefore, not every sentence in our dataset is used in the analysis; every criminal who is incarcerated prior to 2001 recidivates- otherwise we would not observe them. We therefore estimate the correlates of recidivism after a criminal's initial "sample qualifying" sentence (served in Bollate or Opera between 2001 and 2012). However, we will include in our explanatory variables information on incarceration periods accumulated before the qualifying sentence.

Table 2.6 shows the estimated coefficients from a Cox-proportional hazard model of recidivism. Such model allows us to control for the baseline hazard $\lambda_0(t_{i,n})$ in a non-

[8]See Drago et al. (2009) for an excellent quasi-experimental evidence of specific deterrence.

parametric way:

$$\lambda(t_{i,n}|X_{i,n}) = \lambda_0(t_{i,n}) \exp(\alpha_i + \beta' X_{i,n}), \tag{2.1}$$

where i indexes individuals, and n their incarceration.

All the coefficients can be interpreted as semi-elasticities. Before interpreting the results let us highlight that after the sample selection we are left with 6,039 incarcerations and 3,147 individuals, meaning that on average we observe about two incarcerations per inmate. Later, we will exploit the panel dimension in incarcerations and estimate a dynamic hazard model, thus assuming that the individual heterogeneity can be captured by the past duration $T_{i,n-1}$.

The coefficients in column 1 of Table 2.6 are based on the entire sample. Each additional year of age reduces the hazard rate of rearrest by 2 percent. Incarceration length does not seem to influence recidivism, but columns 2 to 5 show that the overall effect hides considerable heterogeneity. Marital status (the excluded category is single) has little predictive power. Having a secondary schooling degree, or providing no information on the schooling degree, seems to be associated to higher recidivism rates (the excluded category is primary schooling). Italians appear to recidivate more, but this should be taken with a grain of salt, as it is more difficult to identify the criminal histories of immigrants.

People who were working in the legal sector prior to incarceration are less likely to recidivate, which is consistent with economic theory. Surprisingly, people who report being unemployed, rather than out of the labor force entirely, are more likely to be reincarcerated, but these effects are not estimated very precisely. And, finally, the type of crime that a criminal participated in also has some predictive power. Those who have been incarcerated for robberies, sexual assaults, and assaults are less likely to end up again in prison, no matter the type crime they committed before being rearrested. While it is tempting to conclude that this is evidence that people who commit robbery are more or less criminal than car thieves, the prevalence of industry switching throughout a career suggests that, perhaps, the predictive power of crime type is to some extent picking up variation in criminal experience.

We now divide our sample of criminals by that criminal experience. As mentioned earlier, two forces are likely pointing in opposite directions. If a longer prison time acts as a specific deterrent, actually lowering the individual's expected net return from crime, we would expect to see less recidivism after longer sentences. At the same time, however, if more prison time allowed inmates to better learn the "criminal" job from fellow inmates and to build networks for future collaborative jobs, we would expect a positive relationship between prison time and recidivism, especially at the beginning of someone's career.

This is precisely what we find. Columns 2 to 5 divide the sample into the number of incarceration quartiles that correspond to 1 to 2, 3 to 4, 5 to 7, and more than 8 incarcerations. Since we are still controlling for crime-types as well as age and experience the coefficient on incarceration length is neither capturing differential hazards across age or experience, nor selection across crime types.

The results are striking: criminals in the first or second incarceration are 6.8 percent more likely to recidivate if they spend an additional year in jail. The effect is 0 in their 3rd and 4th incarceration, but starts being negative after that. In the third quartile the deterrence effect prevails -6.2 percent, and in the last quartile it is predominant (-14.6 percent).

In table 2.7 we go beyond the assumption that $\alpha_i = \alpha$, allowing the individual effect to be persistent over time $\alpha_i = \alpha T_{i,n-1}$, meaning that the previous time to recidivism is assumed to influence the current hazard rate, and thus the current time to recidivism.

Table 2.7 shows that there is indeed a high degree of persistence: longer time to recidivism in the previous incarceration leads to lower hazard rates (-11 percent for each additional year). Controlling for such individual heterogeneity the deterrence effect of the incarceration length becomes quite large (-21 percent for each additional year in jail).

Table 2.6: Cox-proportional Hazard Model of Recidivism

	(1)	(2)	(3)	(4)	(5)
	Hazard rate of reincarceration				
		Incarceration quartiles			
	Full sample	I (1-2)	II (3-4)	III (5-7)	IV (8+)
Age	-0.020***	-0.025***	-0.013**	-0.025***	-0.017**
	(0.003)	(0.005)	(0.005)	(0.006)	(0.007)
Experience	-0.005	-0.033***	-0.013	-0.016	-0.001
	(0.005)	(0.011)	(0.010)	(0.011)	(0.014)
Incarceration length (years)	-0.009	0.068***	-0.005	-0.062*	-0.146***
	(0.011)	(0.018)	(0.022)	(0.033)	(0.039)
Total number of incarcerations	0.070***				
	(0.005)				
In a relationship	0.063	0.088	0.042	-0.088	0.087
	(0.040)	(0.082)	(0.078)	(0.079)	(0.078)
Separated or divorced	0.068	0.182	0.170	0.206	-0.130
	(0.084)	(0.180)	(0.175)	(0.143)	(0.154)
Italian	0.424***	0.559***	0.201**	0.478***	0.041
	(0.053)	(0.078)	(0.095)	(0.127)	(0.118)
College degree	-0.000	-0.198	0.106	0.310**	-0.122
	(0.092)	(0.171)	(0.174)	(0.157)	(0.224)
Secondary schooling	0.127***	0.175**	0.096	0.122	0.057
	(0.045)	(0.082)	(0.095)	(0.093)	(0.088)
Schooling Unknown	0.180***	0.093	0.329***	0.041	0.047
	(0.053)	(0.104)	(0.111)	(0.109)	(0.105)
Employed	-0.045	-0.109	-0.532*	-0.007	-0.081
	(0.132)	(0.272)	(0.312)	(0.265)	(0.256)
Unemployed	0.141	0.006	-0.126	-0.105	0.124
	(0.125)	(0.268)	(0.311)	(0.257)	(0.208)
Employment unknown	0.106	-0.113	-0.233	-0.078	0.175
	(0.120)	(0.255)	(0.298)	(0.246)	(0.202)
Homicide	-0.004	-0.273	-0.064	0.343	0.185
	(0.112)	(0.193)	(0.221)	(0.284)	(0.355)
Assault	-0.121**	-0.176*	0.096	-0.293***	-0.129
	(0.051)	(0.095)	(0.097)	(0.107)	(0.107)
Sex-related crime	-0.389**	-0.296	-0.318	-1.126**	0.314
	(0.192)	(0.335)	(0.273)	(0.480)	(0.525)
Theft	0.107**	0.157*	0.179**	0.287***	-0.000
	(0.047)	(0.090)	(0.088)	(0.095)	(0.101)
Robbery	-0.512***	-0.917***	-0.347***	-0.243***	-0.199**
	(0.040)	(0.076)	(0.072)	(0.085)	(0.088)
Extortion	-0.036	0.073	-0.059	0.137	0.003
	(0.079)	(0.148)	(0.159)	(0.187)	(0.177)
Possession of stolen goods	0.040	0.142	0.165*	-0.193**	0.038
	(0.044)	(0.091)	(0.090)	(0.090)	(0.098)
Drug-related crime	-0.101*	-0.025	-0.069	-0.168	-0.197
	(0.054)	(0.102)	(0.107)	(0.112)	(0.131)
Other crime	-0.046	-0.062	0.068	0.093	-0.108
	(0.057)	(0.113)	(0.115)	(0.117)	(0.125)
Month and year fixed effects	x	x	x	x	x
Observations	6,039	1,670	1,594	1,405	1,370
Number of individuals	3,147	1,413	1,206	878	566
pseudo-R2	0.0181	0.0265	0.00973	0.0174	0.0137

Notes: All regressions control also for year and month fixed effects. Incarceration quartiles are 1-2, 3-4, 5-7, 8 and more incarcerations. Standard errors in parentheses (clustered by individuals): *** p<0.01, ** p<0.05, * p<0.1.

The total number of incarcerations matter as well (+5.7 percent), while having spent jail time for the same crime chosen before does not.

In columns 2 and 3 we divided the sample based on the number of incarcerations. Time to recidivism is more persistent as offenders progress in their criminal career. This could be driven by two forces: selection or change in attitudes. As the number of incarcerations goes up, the criminals who stay active might be of the more persistent type, or they might just become more persistent in their recidivistic behavior if, for example, their legal labor market opportunities have further deteriorated.

Even controlling for the previous time to recidivism, there is strong evidence that over time specific deterrence becomes relatively more important than the criminogenic effect of prison time. After the first 5 incarcerations there is probably little criminal capital left to develop and, conditional on crime committed, we observe each additional year of jail reduces recidivism by 34 percent.

Table 2.7: Dynamic Cox-proportional Hazard Model of Recidivism

	(1)	(2)	(3)
	Hazard rate of reincarceration		
		Incarcerations	
	Full sample	below 5	above 5
Lagged re-incarceration time (years)	-0.112***	-0.035	-0.202***
	(0.022)	(0.029)	(0.038)
Age	-0.013***	-0.011**	-0.018***
	(0.003)	(0.004)	(0.005)
Experience	-0.006	-0.024***	-0.009
	(0.006)	(0.009)	(0.010)
Incarceration length (years)	-0.211***	-0.130***	-0.344***
	(0.027)	(0.038)	(0.041)
Total number of incarcerations	0.057***	0.180***	0.039***
	(0.006)	(0.030)	(0.008)
Persistence across crimes	0.047	0.050	0.037
	(0.041)	(0.056)	(0.060)
Homicide	0.039	0.018	0.026
	(0.198)	(0.223)	(0.390)
Assault	-0.214***	-0.194**	-0.225**
	(0.066)	(0.084)	(0.100)
Sex-related crime	-0.152	0.051	-0.655
	(0.227)	(0.225)	(0.456)
Theft	0.021	-0.032	0.177*
	(0.061)	(0.080)	(0.094)
Robbery	-0.269***	-0.322***	-0.119
	(0.051)	(0.067)	(0.077)
Extortion	0.012	0.039	0.121
	(0.123)	(0.147)	(0.203)
Possession of stolen goods	0.102*	0.059	0.130
	(0.056)	(0.077)	(0.079)
Drug-related crime	-0.036	-0.146	0.174*
	(0.068)	(0.095)	(0.093)
Other crime	-0.035	-0.105	0.141
	(0.072)	(0.098)	(0.108)
Month and year fixed effects	x	x	x
Other Xs	x	x	x
Observations	3,997	2,120	1,877
Number of individuals	2059	1394	878
pseudo-R2	0.0157	0.0138	0.0193

Notes: All regressions control also for year and month fixed effects. Standard errors in parentheses (clustered by individuals): *** p<0.01, ** p<0.05, * p<0.1.

2.4 Conclusion and Policy Implications

This chapter has shown that criminal careers display a high degree of heterogeneity in terms of when they start, how they evolve, and how they end. Criminals usually start their careers around the age of twenty and stay on average criminally active for at least 8 years. They are more likely to have low levels of education and to be unemployed or out of the labor force. This is probably why many of them seem to start their careers in the south of Italy, where labor market prospects are quite meager, and later move to the north. These patterns suggest that the current economic crisis, which between 2008 and 2012 reduced real GDP by 6 percent, might exacerbate the positive trend in crime rates, which, we show, started in the mid-nineties.

In terms of evolution, criminals are more likely to start their careers with a drug-related crime or with simple theft than to end their career with such crimes. Participation in a crime like murder or robbery is more likely to signal someone at the end of their career. In terms of transiting across different types of crimes, the probability of specializing, by choosing the same crime across subsequent incarcerations, is increasing with experience, especially for robbers. This suggests that we should use persistence in the choice of the crime type to predict the experience level of robbers.

Understanding the end of a criminal career is likely to be the single most important way to design policy interventions aiming at reducing crime rates among ex-convicts. The panel dimension with respect to incarcerations allows us to highlight the most important predictors of recidivism. We confirm that recidivism goes down with age and experience, while the total number of incarcerations is positively associated with recidivism. Incarceration length has a negative effect on recidivism only after the first two incarcerations, suggesting that the initial incarcerations represent a crime school for inmates.

If one had to use this evidence to design optimal sentencing guidelines, sentences should be longer as the number of previous incarcerations increase, and as the previous time to reenter jail decreases. Conditional on the number of incarcerations, jail time should decrease with age and experience, as both predict retirement from criminal jobs. The Italian criminal law does indeed contain sentencing guidelines that are approximately consistent with these predictions. First-time offenders are unlikely to serve time in prison, and so are criminals that are above age 65.

Before December 2005 recidivists could get a 1/6th increase in their sentence, but judges would often weigh recidivism against the mitigating circumstances reducing its impact on the total sentence. Since 2006 (law n. 251, called "ex-Cirielli") recidivists can get up to 1/3 longer sentences, and multiple-recidivists up to 2/3 longer sentences. Moreover, the new law reduced the discretionary power of judges when dealing with recidivists.

By regressing the log-incarceration length on the same variables that predict recidivism and by comparing the sign of the coefficients we can assess whether sentencing guidelines appear to be consistent with an optimal sentencing design. We should expect a negative coefficient on age and experience and a positive one on the total number of incarcerations, but Table 2.8 shows that the opposite is true. Given that the 2005 ex-Cirelli law introduced considerably harsher punishments for multiple recidivists in Column 1 we control for a multiple recidivist (more than two time recidivists) dummy as well for the interaction between this dummy and a post January 2006 dummy (the post 2006 dummy is being absorbed by the entry year fixed effects). There is clear evidence that with the new law multiple recidivists receive sentences that are 25 percent higher than before, while before the law their sentences were not statistically different from those who were not multiple recidivists.

The only variable that predicts recidivism and longer sentences is the previous re-incarceration time, but the effect is not statistically different from zero. Given the non-experimental design of this analysis we need to be cautious when interpreting these effects, as they might in part be driven by variation in the severity of crimes within each crime category.

Table 2.8: Log-Incarceration Length

	(1)	(2)
	Log-Incarceration length	
Multi-redivist	0.058	
	(0.042)	
Multi-recidivist x post 12/2005	0.260***	
	(0.081)	
Lagged reincarceration time (years)		-0.063***
		(0.020)
Experience		0.060***
		(0.006)
Total number of incarcerations	-0.011**	-0.055***
	(0.006)	(0.007)
Single	0.062	0.144*
	(0.072)	(0.076)
In a relationship	0.057	0.060
	(0.075)	(0.081)
Separated or divorced	-0.101	0.022
	(0.097)	(0.115)
Italy	0.133***	-0.031
	(0.043)	(0.059)
Age	0.021***	0.000
	(0.002)	(0.003)
College degree	0.388***	0.422**
	(0.144)	(0.214)
Secondary schooling	0.408***	0.403**
	(0.127)	(0.188)
Primary schooling degree	0.409***	0.452**
	(0.130)	(0.193)
Schooling Unknown	0.495***	0.544***
	(0.132)	(0.189)
Employed	0.052	0.161
	(0.113)	(0.156)
Unemployed	0.158	0.263*
	(0.110)	(0.149)
Employment unknown	0.234**	0.337**
	(0.106)	(0.140)
Homicide	0.408***	0.480***
	(0.072)	(0.181)
Assault	0.245***	0.343***
	(0.036)	(0.055)
Sex-related crime	0.641***	0.754***
	(0.113)	(0.181)
Theft	0.391***	0.649***
	(0.035)	(0.051)
Robbery	0.959***	0.911***
	(0.032)	(0.045)
Extortion	0.281***	0.398***
	(0.053)	(0.090)
Possession of stolen goods	0.436***	0.503***
	(0.034)	(0.052)
Drug-related crime	0.575***	0.704***
	(0.039)	(0.060)
Other crime	-0.068	0.106
	(0.049)	(0.071)
Entry year FE	yes	yes
Observations	11,314	6,325
R-squared	0.348	0.190

Notes: The regression controls for year fixed effects, education, and employment status. Standard errors in parentheses (clustered by individuals): *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

The Robbery Sector

The previous sections allowed us to pinpoint the most prolific criminals, defined as those who are more likely to recidivate, and those who recidivate more quickly. Previous criminal behavior, age, and experience were shown to be important predictors of criminogenic behavior. But judges not only observe the criminals individual characteristics and crime type, they also observe and might exploit the information contained in the *modus operandi* of these crimes. While the prison data do not contain information on the *modus operandi*, the police data do.

3.1 The Police Data

Since 2007, the police department of Milan, following the lead of officer Mario Venturi, has collected data on all robberies that occur within their jurisdiction, gathering information from victim interviews and surveillance-camera footage. For each robbery, the dataset records information about the crime itself (time, date, location, type of business, etc.), about the criminals (age, height, body structure, skin, hair, eye color, etc.), about the weapons (type, maker, model, color), and about the vehicle used (type, maker, model, license-plate, etc.). The police department uses special software capable of analyzing these data in particularly useful ways. Robberies that have at least one robber, weapon, or vehicle in common are identified as being part of the same "series," and are considered to be linked, rather than independent and isolated criminal events.

In addition to eventual use by prosecutors, the police are able to use this information to prevent crime. Observed patterns in past robberies are used to predict future potential targets. Individual police patrol units are notified of any specific business or general location that is identified as a likely robbery victim, along with any time or day of the week that a set of robbers are likely to strike. This procedure is has become known as "predictive policing."

We have been given access to a subset of this predictive policing data set, which contains data on all commercial robberies taking place in Milan between 2008 and 2011. For each robbery, we observe basic information about the incident, such as the time, date, and victim, along with the amount of money stolen, whether or not an arrest was eventually made "clearing" the robbery, and how many robbers participated in the criminal act.

Figure 3.1 shows that most robberies take place on Mondays and Fridays- just before and just after the weekend. There are very few robberies on Sundays, which is not surprising given that many businesses are closed (i.e. banks, postal offices, etc.). Robberies also display a remarkable seasonality; they are considerably more frequent in the winter, and reach their minimum between June and August. The ratio between the number of robberies in winter and in the summer is almost 2 to 1. While the drop in August could be explained by the fact that many businesses are closed in that month, the reason for the low robbery rates in the other summer months is less obvious.

We also observe limited information about the individual robbers- whether or not each perpetrator was armed, whether they were male or female, and how roughly old they were at the time of a given robbery. Most importantly, our data indicates whether or not each robbery was believed to be an isolated act, or part of a series of robberies committed

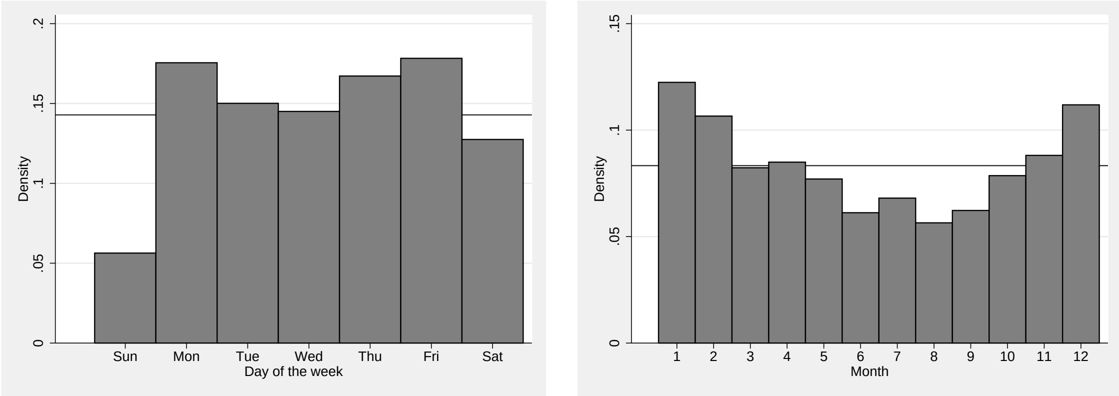

Figure 3.1: Distribution of Robberies by Day of the Week and Month

Notes: The vertical lines indicate how a uniform probability distribution would have looked like. The distribution of months does not include data on 2011, since that year robberies are only observed until June.

by a set of connected criminals. According to the Milanese police, 70 percent of these robberies are part of a series; the longest series in these data contains 49 robberies.

As can be seen in Table 3.1, there are 2,165 robberies recorded in the data we use (each observation represents one robbery). Just under 14 percent of robberies are cleared before a new robbery is organized, which typically occurs when one or more robbers involved in it are identified and arrested- but clearing one robbery often allows prosecutors to attribute past robberies to the arrested offenders, increasing the overall clearance rate. About 73 percent of robberies take place in zones that are under the jurisdiction of the Polizia, which is roughly consistent with the fraction of Milan under Polizia supervision at any given time. Approximately 80 percent of robberies are initially successful, in the sense that robbers capture some loot. The distribution of captured loot is highly skewed- the largest haul is over €100,000, but on average about €2,800 is stolen.

Robbers frequently work in teams; 45 percent of robberies are committed by more than one person and the mean number of robbers participating in a given event is about 1.5. The "first," or most dangerous robber is armed 44 percent of the time, is roughly 31 years old, and is almost always (99.7 percent of the time) male. Larger groups of robbers tend to have fewer weapons per person, and are also slightly older on average. Larger

Table 3.1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Number of robbers	1.57	0.716	1	7	2,165
Cleared robbery	0.139	0.346	0	1	2,165
Police 0/1	0.732	0.443	0	1	2,165
Amount stolen in euros	1,630	5,494	0	103,000	2,165
Loot with some value	0.808	0.394	0	1	2,165
Age of robber 1	31.43	8.231	16	68	1,936
Age of robber 2	29.256	7.709	16	65	735
Age of robber 3	30.274	10.297	16	55	84
Age of robber 4	29.786	10.431	18	50	14
Age of robber 5	33.167	16.29	18	60	6
Age of robber 6	32	12.728	23	41	2
Average age	26.572	12.471	0	68	2165
Range in age	1.221	3.99	0	43	2165
Robber 1 is armed	0.438	0.496	0	1	2,165
Robber 2 is armed	0.091	0.287	0	1	992
Robber 3 is armed	0.05	0.219	0	1	160
Robber 4 is armed	0.029	0.169	0	1	35
Robber 5 is armed	0	0	0	0	9
Robber 6 is armed	0	0	0	0	2
Female robber 1	0.003	0.057	0	1	2,164
Female robber 2	0.017	0.13	0	1	991
Female robber 3	0.025	0.157	0	1	159
Female robber 4	0.029	0.169	0	1	35
Female robber 5	0	0	0	0	9
Female robber 6	0	0	0	0	2

robbery groups are also more likely to have women in them, although this is still quite uncommon.

The high rate of co-offending in Milan is not that unusual- according to the U.S. National Crime Victimization Survey, 41 percent of robberies were committed by multiple offenders in 2008- but it does mean that typical economic models of crime, which are based on individual decision making, may not be sufficient to characterize the robbery industry. Instead, we will conceptualize robbery "sets" as illegal firms, and use insights on worker-firm dynamics and firm productivity to analyze this particular type of crime.

3.2 The Economic Value of Illegal Firms

Before describing the strategies of the groups of robbers in our sample, it is useful to present a reference framework to understand the typical trade-off that these criminals face. We define an illegal robbery "firm" as an organization that produces at least one robbery. These illegal firms can add or subtract workers indefinitely, as long as the Milan police continue to attribute additional robberies to that specific series. A robber who works alone is labeled a "self-employed" robber.

One particular benefit of thinking about robbery sets as firms, rather than individuals, is that it simplifies the optimization problem facing the group. Later in the chapter, we will use the assumption of the profit maximizing firm to back out the revealed cost of punishment, and thus underlying productivity, of illegal organizations.

The optimal strategy of any firm, legal or illegal, is one that maximizes their economic value, or profit. Just as legal firms do, illegal firms have to invest in capital, hire workers with a particular set of skills, and decide what to produce, in order to maximize the difference between their revenues and costs. Unlike legal firms, illegal firms face not only standard production costs, but also must contend with several actors who try to impede production- the criminal law, law enforcement agencies, and potential victims are constantly trying to counteract illegal activities. All of these counteracting agents try to reduce the profitability of an illegal firm by increasing the certainty and severity of crime, increasing the cost of business, or by reducing cash holdings or hiring armed guards, reducing the potential firm revenue.

We define the probability that an illegal firm i is successful in a given robbery as $1-p\left(x_i\right)$, meaning that the firm is able to capture a non-zero amount of loot equal to $Y\left(x_i\right)$. The firm's expectation of the loot is $\widehat{Y}(x_i)$. The vector x_i represents both observed and unobserved characteristics of the firm that affect it's ability of extract revenue and reduce costs. The costs facing firm x_i are defined as punishment S, which is imposed on the firm by the criminal justice system, and disrupts the firm's operations for a number of years. The cost of such disruptions is equal to the potential earnings $D(S(x_i))$ that the firm would have been able to acquire, and is essentially the opportunity cost of foregone illegal production. The probability that firm i receives punishment $S(x_i)$, costing $D(S(x_i))$, after a robbery is $p(x_i)$, since for practical reasons all arrests lead to lengthy incarcerations (according to the Milan police only one defendant was not found guilty). This leaves us with the following production decision rule for illegal firms:

$$\Pi_i = [1 - p(x_i)] \widehat{Y}(x_i) - p(x_i) D(S(x_i)) \geq 0$$

$D(S(x_i))$ depends on the yearly productivity of firms d times the number of years $S(x_i)$ operations would be disrupted for a firm operating with characteristics x_i.[1]

Ideally, the government should set the expected cost of punishment to be a positive function of the ability of the illegal firm, as this would deter the most socially harmful illegal activity. Consistent with this, we allow law enforcement to partially influence two variables in this equation $p(x_i)$ and $S(x_i)$ in a way that target the behaviors that signal such abilities. Of course, law enforcement can set sanctions S, such that they depend on a subset of the modus operandi $x_s \subseteq x$. For example, armed robbers are typically more heavily sanctioned than robbers who do not use weapons. Single, self-employed robbers also typically receive shorter sentences than those in multi-person firms. Law enforcement is prohibited for sanctioning robbers more or less heavily based on nationality, gender, or the area the criminals decide to target for their illegal activity, even if these factors are correlated with the firm's productivity. However, police can vary the amount of resources they invest in finding a particularly profitable firm, increasing $p(x_i)$.

As in any industry with reasonably free entry, in equilibrium economic profits will be equal to zero. For our purposes, this means that we can specify the foregone earnings of

[1]Here we are implicitly assuming that there is no discounting. Incorporating some discounting is not going to substantially change the analysis.

any firm, if punished, as

$$D(S(x_i)) = \frac{1 - p(x_i)}{p(x_i)} E[Y(x_i)]. \tag{3.1}$$

Taking the log of foregone earnings, which happens to make particular sense in Italy as sentence enhancements are often proportional to the minimum sentence, allows us to simplifying the notation, $\log D(x) = \log\left[\frac{1-p(x)}{p(x)}\right] + \log \widehat{Y}(x)$. In order to describe the way the modus operandi is associated with the value of the firms production we can derive D with respect to x, $\frac{\partial \log D}{\partial x}$.

Given that $D(x)$, $\widehat{Y}(x)$, and $p(x)$ are all equilibrium outcomes, the derivatives of such outcomes cannot be given any causal interpretation. In fact, one should expect that if there is free entry into the market for robbers, partial derivatives of $D(x)$ with respect to any element of x_i that are not equal to zero suggest that firms are not operating efficiently.

For example, suppose there is an area in the city of Milan where criminal firms' revenues are significantly larger. Since sentences cannot depend on the area where the crime has been committed (i.e. $S(x)$ is constant with respect to geography), it must be true that in the same area the likelihood of arrest is larger (i.e. $p(x)$ is greater in that area), otherwise most firms would decide to target businesses in that same area. At the same time, suppose there is a particular criminal strategy that increases the revenues and at the same time reduces the likelihood of arrest, like for example the use of firearms. Then it must be true that law enforcement sets the expected sanctions in order to compensate such advantage, otherwise all firms would switch to that same strategy. We are going to come back to this idea when discussing the results.

Let us now be a little more formal, starting with the xs, x_S, that can be manipulated by law enforcement to change the severity of punishment $S(x)$, like how much to punish the use of firearms. For simplicity we take derivatives, even when changes for a particular variable are discrete.

Setting the derivative of the expected profits Π with respect to x_S equal to zero:

$$\frac{\partial \Pi}{\partial x_S} = -p(x) \frac{\partial D(S(x))}{\partial S(x)} \frac{\partial S(x)}{\partial x_S} = 0,$$

or, using a simplified notation and the fact that $p(x) > 0$, $D_{x_S}(x) = 0$.

Given that these are equilibrium outcomes one needs to make sure that policy makers have enough time to adjust the sanctions to disincentivize successful strategies.

Setting the derivative of the expected profits Π with respect to x_p, meaning those policies that try to avoid arbitrage opportunities in location, time, and victims type, equal to zero is a little more cumbersome, but leads to the same result. Such changes influence $p(x)$ and $Y(x)$:

$$\Pi' = -p'(x)(\widehat{Y}(x) + D(x)) + (1 - p'(x))Y'(x) = 0.$$

Making use of the zero profit condition one can show that the condition simplifies again to the previous condition, meaning that $D_x(x) = 0$, or $\frac{D_x(x)}{D(x)} = 0$. Given that $\frac{D_x(x)}{D(x)} \approx \frac{\partial \log D(x)}{\partial x}$ it is again convenient to select a specific functional form for $p(x)$ and for $\widehat{Y}(x)$, namely logit $p(x) = \frac{exp(x'\beta_x^p)}{1-exp(x'\beta_x^p)}$ and log-linear $\widehat{Y}(x) = x'\beta_x^Y$. With such a choice the derivative is equal to

$$\frac{\partial \log D}{\partial x} = \beta_x^Y - \beta_x^p,$$

and does not vary across criminal gangs.

The intuition of this condition is straightforward. In the dimensions x where law enforcement and criminal gangs interact with each other, any productivity gain in $Y(x)$ has to be counterbalanced with a productivity loss in $p(x)$. While the changes in revenue and costs are of independent interest, our estimates of the foregone earnings of disrupted firms will allow us to make broader statements about what observable characteristics are hallmarks of productive illegal organizations.

3.3 Productivity of Legal vs. Illegal Firms

Arguably one of the most enduring questions in macro and labor economics is the determinants of firm productivity- why is it that, given similar access to resources and a market competitive environment, is there such variation in the productive capacity of organizations? In the legal sphere, the increased prevalence of detailed, employer-employee matched data sets has allowed researchers to observe increasing detailed information about workers and the firms that employ them. Still, there are surprisingly vast and unexplained productivity differences across firms. In a recent survey, Syverson (2011) suggest that a US plant in the 90th percentile of the productivity distribution is on average, twice as productive as a plant in the 10th percentile of the distribution of the same industry (Syverson, 2004). Evidence from developing countries suggests that the dispersion in productivity across firms is at least twice as large Hsieh and Klenow (2009).

Anticipating some of our later results, parametric estimates of Eq. 3.1 can be used to construct the distribution of productivity across illegal firms, presented in figures 3.2 and 3.3. As in the legal sector, there are large differences in firm productivity, with an order of magnitude, approximately €75,000, in profit separating the 90th and 10th percentiles of the distributions. The predictive policing data from Milan offers us a unique opportunity to explore the possible predictors of criminal ability.

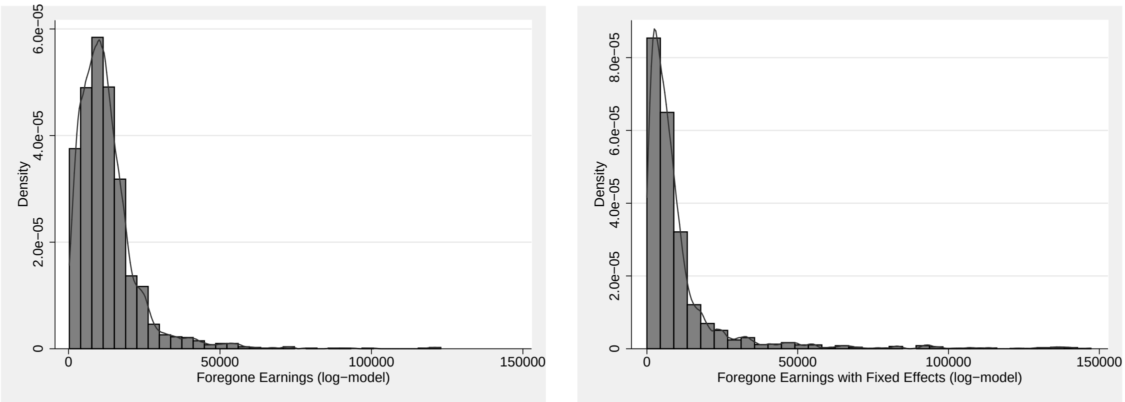

Figure 3.2: Foregone Earnings Without (left) and With (right) Firm Fixed Effects

Notes: The histogram and the kernel densities are based on estimates of Eq. 3.1. The firm fixed effects are based on the log-haul model.

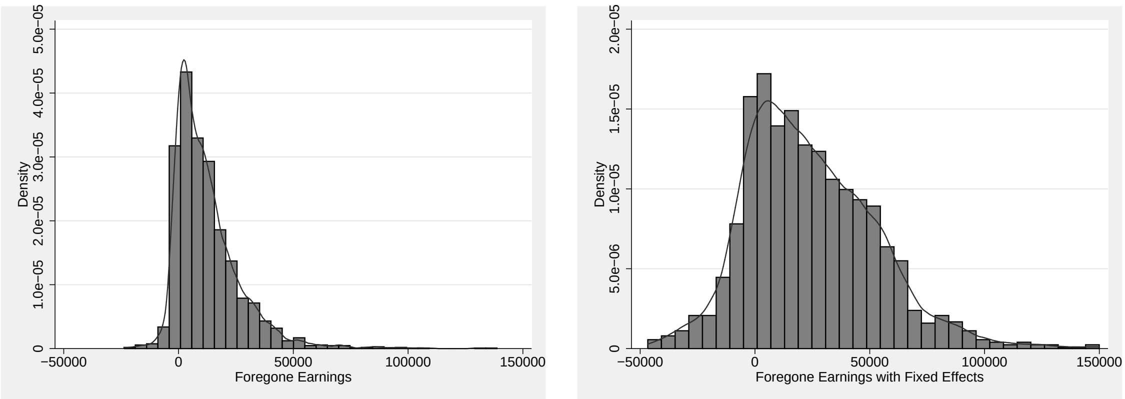

Figure 3.3: Foregone Earnings Without (left) and With (right) Firm Fixed Effects

Notes: The histogram and the kernel densities are based on estimates of Eq. 3.1. The firm fixed effects are based on the haul model in levels.

3.3.1 Non-parametric Evidence on Productivity

As shown in the previous section, the estimated value of production in Eq. 3.1 represents a synthetic measure of a given firm's underlying productivity. Such productivity is going to depend on observable as well as unobservable characteristics of criminal firms, x_i. Temporarily setting aside issues of unobserved heterogeneity in productivity across firms, in this section we will provide a purely non-parametric description of variation in productivity across firms. We will describe the likelihood of arrest p, the average loot $\widehat{y}$, the expected average loot $(1-p)\widehat{y}$, as well as the value of production $(1-p)\widehat{y}/p$, across many different characteristics of firms and victims.

We will also highlight current "best estimates" of the determinants of firm productivity from the legal sector, with particular emphasis on recent empirical contributions using employee-employer matched data. Recent results from the traditional labor and macroeconomic literature will guide our analysis, which will focus on firm size, monitoring costs, worker age, access to capital, informal networks and specialization in production.

3.3.2 Growth and Change in Illegal Firms

Small firms dominate both legal and illegal sectors; according to the 2007 US economic census, 38 percent of all legal establishments were in firms with 4 or fewer employees (the smallest firm size recorded), and recall that in equilibrium, just over 1/2 of the illegal firms will consist of "self employed" workers. The number of illegal firms is also strictly decreasing in number of robbers; only 9 firms with five or more workers are observed. In contrast, the distribution of legal firms is bimodal- there are very few establishments in 500 to 2,500 worker firms, but almost 10 percent of all establishments are in firms with more than 2,500 employees. This second local maximum is consistent with increasing returns to scale in some industries, or large scope for technological innovation and worker specialization that can make the net relationship between output per worker and the number of workers positive (Idson and Oi 1999). Of course, the exclusion of illegal firms from credit markets means that large technological investments will typically be out of reach for most groups of robbers. However, even if illegal firms had access to credit markets, illegal firms may be less able to sustain a large workforce for other reasons.

The growth and contraction of robbery firms is clear in Table 3.1, which shows the joint distribution of firms size in the current robbery and in the previous robbery in the firm's series. Most firms are small; the average number of robbers in any given robbery is between 1 and 2, but these simple averages hide considerable variation, both in the cross-section and over time. Overall, Table 3.2 suggests that between any two robberies, there is at least 25 percent chance that the firm will grow or shrink (any off-diagonal element represents a change in the size). [2]

More specifically, of the 681 robbery firms that begin as single worker firms, 104 add another worker by the next robbery, 6 will add two people, and 1 firm will add 3 workers in the next event. The majority (352 out of 505) of two person firms will keep the same number of workers in the next robbery, but roughly 1/5th will shrink, and 48 will continue to grow in the next period. Notably, firms with more than 3 people appear to be highly unstable, with most (32 out of 52) only having two members in the next event. As we will discuss in more detail later in this chapter, this instability is consistent with heightened monitoring and coordination costs associated with illegality.

The joint distribution of firm size can be used to calculate the transition matrix of firms, meaning the conditional distribution of firm size based on the size in the previous period. Since there are no firms of size 5 and 6 in period 2 we restrict the transition

[2]The nationalities of robbers also tends to change across robberies, though to a lesser degree than the size of the firm. Results are available upon request.

Table 3.2: Evolution of the Size of Firms

	Lagged number of robbers				
	1	2	3	4	Total
N. of robbers					
1	570	105	3	2	680
	(45.45)	(8.37)	(0.24)	(0.16)	(54.23)
2	104	352	32	8	496
	(8.29)	(28.07)	(2.55)	(0.64)	(39.55)
3	6	36	12	3	57
	(0.48)	(2.87)	(0.96)	(0.24)	(4.55)
4	1	8	5	2	16
	(0.08)	(0.64)	(0.40)	(0.16)	(1.28)
5	0	3	0	1	4
	(0.00)	(0.24)	(0.00)	(0.08)	(0.32)
6	0	1	0	0	1
	(0.00)	(0.08)	(0.00)	(0.00)	(0.08)
Total	681	505	52	16	1,254
	(54.31)	(40.27)	(4.15)	(1.28)	(100.00)

Notes: Frequencies and relative frequencies in parentheses.

matrix to be of size 4×4, where the last column/row represents a size of *at least* 4.

$$T = \begin{pmatrix} 0.837 & 0.208 & 0.058 & 0.125 \\ 0.153 & 0.697 & 0.615 & 0.500 \\ 0.009 & 0.071 & 0.231 & 0.188 \\ 0.001 & 0.024 & 0.096 & 0.188 \end{pmatrix}$$

In this matrix, element t_{rc} measures the likelihood of moving from size c to size r. One can easily compute its steady state equilibrium distribution p such that $pT = p$, which is (0.537 0.397 0.047 0.018). This number is not very different from the marginal distributions of size, indicating that the dimension of most firms is in a steady state.

Several interesting facts about the evolution of illegal firms emerges from matrix T. Note that three person are more likely to shrink in the next period than maintain the same number of workers. At the same time, multi-worker firms rarely transition to single worker firms. While it appears to be difficult to maintain a large illegal group for multiple robberies, based on the revealed firm transitions, it does appear to be the case that working as a group provides some benefit that individual robbers cannot obtain on their own; people who commit a group robbery in one period are unlikely to commit robberies on their own in the future. Only 20 percent of two-worker firms will become "self-employed" in the next robbery, 6 percent of three-worker firms will transition to self-employment, and 12 percent of larger firms will transition to single employee firms in the next robbery.

Productivity and Firm Size

Firms should hire additional workers until the marginal revenue product of an additional employee is identical to the total cost of hiring that worker, in terms of both actual salary and forgone marginal revenue product of capital investment. Compared to firms that operate in the legal sector, the marginal revenue product of an additional employee will fall faster in illegal firms, and the marginal cost of hiring an additional worker will rise faster.

In a basic Salop-circle style model of firm size, marginal revenue product will be decreasing in firm size if the last worker hired is the least productive, or the worst "match," in a given firm. Shirking can also explain the shrinking marginal return, to the extent that monitoring costs grow as more employees are hired. In a cross sectional sense, firms that employ more workers do typically have lower levels of output per worker (Foster et al., 2001, Haltiwanger et al., 2011).

While both match quality and monitoring costs limit the size of all firms, monitoring costs are likely to be more important in illegal businesses. This follows from the idea that a supervisor's ability to monitor an illegal employee is positively correlated with a police officer's ability to monitor the employee (Reuter, 1985). While we cannot distinguish employees from employers, the public good aspect of the economic value of a firm means that, in this context, all workers must monitor each other to prevent shirking. By way of example, if a robber evaluated a potential target in a way that was readily observable to other group members, it is also likely that a nearby policeman might also notice, and intervene in the illegal operation.

In the legal sector, firms can structure employee compensation in a way that incentives poorly monitored workers to exert effort, e.g. with an efficiency wage, or by making workers residual claimants. We do not observe any information on the hierarchical or compensation structure within the illegal firm, so we assume that all workers are residual claimants, earning 1/n of the ex-post loot of each robbery, where n is the number of robbers in the firm. While this assumptions means that we will not consider how illegality affects principle-agent problems in firms, it is the case that the return to any particular robbery is a public good, in the sense that a given robber's effort will generate loot that must be shared with his partner(s). As described in Olson (1965), the positive consumption externality of any individual's effort will tend to induce free riding in the absence of monitoring, even if the worker's wage is a function of individual effort.

In addition to high monitoring costs lowering the marginal revenue associated with additional workers, the direct cost of hiring an additional employee in the illegal sector is also likely to be higher. Specifically, in addition to wages, the cost of hiring a new employee increases the probability that the firm will be caught by police. Particularly if police place a high value on capturing as many robbers as possible, a member of a large illegal firm will have an incentive to "snitch" and reveal the identity and actions of their coworkers to the authorities (Reuter, 1985).

Table 3.3 breaks down average loot, clearance rate, expected loot, and foregone earnings by the number of robbers that participate in a robbery. When there is only one robber, the average loot is small (€1,264) and the clearance rate is in relatively large (there is a 16.3 percent chance of getting arrested). The foregone earnings of a self-employed robber are €6,422. With the addition of one more worker to the firm, the average loot increases by over 46 percent, rising to €1,843, and the clearance rate drops from 0.164 to 0.102, while the foregone earnings go up more than 150 percent to €16,162. Such a jump is also consistent with longer disruptions of production when two or more robbers are involved, as such a condition is likely to trigger a sentence enhancement (see Mastrobuoni, 2011).

Although increasing the number of robbers to three raises the clearance rate to 0.133, the average loot also raises to €3,498 per worker; this makes the expected loot with three robbers the highest over all the gang sizes. Three robbers also means a marginal increase, to €22,838, of foregone earnings if caught. Interestingly, but perhaps due to sample size, the risk of arrest falls again once a forth robber is added to a gang (10.7 percent). With five or six robbers, keeping in mind that very few firms have so many "workers," the chance of arrest balloons and the average loot per worker drops to €281 and €25, while the foregone earnings drop to €375 and €25 respectively.

Table 3.3: Productivity by Firm Size

	Average Loot		Clearance Rate		Expected Loot	VoP	
Number of Robbers	Mean	Std. Dev.	Mean	Std. Dev.			Freq.
1	1264	4077	0.164	0.371	1,056	6,422	1,149
2	1843	6448	0.102	0.303	1,654	16,162	850
3	3498	8594	0.133	0.341	3,033	22,838	128
4	2188	5741	0.107	0.315	1,954	18,234	28
5	281	395	0.429	0.535	161	375	7
6	25	35	0.500	0.707	13	25	2
7	0	0	0	-			1
Total	1631	5494	0.13857	0.34558	1,405	10,137	2,165

Notes: VoP stands for value of production, and is equal to $E(Y)(1-p)/p$.

Thus, in the illegal sector, the total revenue per worker is largest for three person groups, implying that, at least over some range, there are increasing returns to scale. We observe only 28 four-person firms, but these organizations appear to be very successful at avoiding capture, with just over 10 percent of robberies resulting in arrest. However, consistent with the previously discussed theory, the per-capita returns to additional workers appears to decline rapidly for groups larger than four. Not only are the larger groups less effective at capturing revenue than smaller firms, these groups are also significantly more likely to be caught by police. Both the high arrest rate and the low revenue rate could be explained by individual workers shirking in these large groups, which is also a potential problem for legal firms. Increasing costs due to increased police attention is a unique problem for illegal businesses.

Specialization and Start-Up Costs

Just as individual criminals may specialize or move in and out of the robbery sector, robbery organizations can specialize in the type of victims that they target. In Milan, 16 different types of victims are selected 15 times or more. Each of these targets is associated with a different menu of start-up costs, potential revenue, or legal risk, and in equilibrium firms with different levels of intrinsic productivity will choose different targets.

In the legal sector, start-up costs are often thought of as the fixed cost of production. In our case, we use planning time a proxy for start-up costs of production, which could include identifying a suitable target, potentially in a in a particular part of town, and identifying the time of day where the expected value of the robbery is highest. The victim's investment in protection is also a key determinant of the start-up cost of production and the potential revenue associated with robbing that particular business. Investments in protection might include storing large amounts of money in vaults that are difficult to access, hiring private security guards, or adding time locks to limit the immediate availability of cash.

Businesses that keep large amounts of cash or valuables on site, such as banks or jewelry stores, are likely to coordinate with the police in a way that increases the likelihood that a successful robbery will result in an arrest. Examples of this could include silent alarms that directly alert the police of a robbery in progress or installing security cameras. Police are also likely to devote more attention to these types of robberies than lower value targets like drug stores.

For sake of space, we will focus our descriptive non-parametric analysis of victim choice on the three most popular targets are pharmacies, supermarkets, and banks.

Table 3.4: Productivity by Target

	Average Loot		Clearance Rate		Expected Loot	VoP	Planning time	
	Mean	Std. Dev.	Mean	Std. Dev.			(days)	Freq.
Bank	6,924	12,671	0.249	0.433	5,201	20,890	30.2	237
Betting Agency	3,334	3,645	0.100	0.303	3,001	30,006	15.8	50
Cellphone Store	300	553	0.133	0.352	260	1,949	2.4	15
Clothing Store	520	910	0.143	0.354	445	3,117	15.5	49
Coffee Shop	1,453	2,761	0.074	0.263	1,346	18,306	16.3	68
Drugstore	648	568	0.038	0.196	623	16,203	35.4	26
Gas Station	2,199	3,353	0.032	0.180	2,128	65,956	15.1	31
Jewellery	3,756	12,157	0.208	0.415	2,974	14,273	38.5	24
Newspaper Stand	1,081	3,013	0.085	0.282	989	11,624	25.8	47
Other Business	1,223	4,401	0.193	0.396	986	5,098	21.6	305
Pharmacy	559	1,498	0.123	0.329	490	3,978	11.4	763
Phone Center	2,113	4,645	0.042	0.204	2,025	48,589	8.6	24
Postal Office	3,748	10,136	0.130	0.344	3,259	24,984	18.6	23
Restaurant	538	1,003	0.182	0.392	440	2,423	29.9	33
Supermarket	955	3,009	0.112	0.316	848	7,563	21.3	348
Tobacco Shop	1,203	1,474	0.085	0.281	1,101	12,992	7.1	59
Video Rental	163	94	0.065	0.248	152	2,358	6.8	62
Overall	1,631	5,496	0.139	0.346	1,405	10,135	16.8	2164

Notes: VoP stands for the value of production, and is equal to $E(Y)(1-p)/p$.

Banks are lucrative targets in terms of revenue, yielding almost €7000 in loot on average. However, the cost of robbing a bank is high as well, and appears to require almost a month of planning time, on average. For firms that invest in these high start-up costs, the marginal cost of production appears to be high; one in four bank robberies result in an arrest, no doubt due to additional police scrutiny and investments in protection made by these victims.

Robbing a pharmacy, on the other hand, is a low-revenue, but also low-cost operation. These victims yield little revenue on average, only €560, but also involve one third the start-up costs, and pose one half the expected arrest risk of bank robbery. These lower costs mean that, while the revenue associated with robbing a bank is 12 times the revenue associated with robbing a pharmacy, the implied productivity of bank robbers is only 5 times the implied productivity of workers who target pharmacies.

Supermarkets are the second most commonly selected robbery victims. Robbers who target supermarkets typically take 20 days to prepare for a robbery that will yield €1000 in additional revenue per person. While this is much less than the return to a bank robbery, only 11 percent of supermarket robberies result in arrest. In other words, the start-up costs associated with planning a supermarket robbery are higher than a pharmacy robbery, but the risk of arrest is roughly the same. The implied productivity of robbers who target grocery stores is about on half of bank robbers, but higher than for pharmacy robbers.

There are striking returns to specialization with regard to victim choice. In table 3.5, it is clear that persistence pays in the robbery sector. Groups that repeatedly target banks capture almost twice the revenue as groups engaged in a bank robbery for the first time, and are 14 percentage points less likely to be arrested. We observe similar, although smaller, increases in revenue and arrest risk for firms that specialize in robbing supermarkets or pharmacies. Firms that specialize in these types of victims are able to capture about €100 more loot, and around roughly 6 percentage points less likely to be arrested than first-timers. The relationship between startup costs and specialization is not the same across these common victims. One of the gains from specializing in robbing pharmacies and supermarkets is a reduction in planning time of roughly 5 days. Firms that target banks, however, appear to take longer to plan than firms robbing a bank for the first time. This interesting result, which stands in contrast to the observed pattern for firms specializing in lower-level targets, is consistent with the true return to planning being something that a bank robber learns over time.

Overall, firms that specialize in robbing grocery stores or pharmacies are twice as productive as firms robbing a grocery or pharmacy for the first time. Firms that repeatedly target banks are almost four times are productive. This is consistent with the legal sector, where longer-lived firms are, on average, more productive than new industry entrants in a given sector (Foster et al., 2001). As in the legal sector, this apparent increase in productivity is likely due to both selection (as the worst robbery groups are most likely to be arrested after any given robbery) and actual productivity growth of a given firm.

Table 3.5: Productivity by Target and Experience

	Average planning time		Average loot		Clearance rate		Value of production		N.Obs	
	New target	Old target	New target	Old target	New t.	Old t.	New t.	Old t.	New t.	Old t.
Bank	22	31	4,104	7,637	0.35	0.21	7,621	29,183	20	135
Betting Agency	12	20	1,948	2,781	0.16	0.07	10,387	36,149	19	14
Cellphone Store	2		90		0.20		360		5	0
Clothing Store	4	58	954	707	0.00	0.00			15	4
Coffee Shop	11	27	1,315	361	0.18	0.13	6,134	2,526	17	8
Drugstore	37	17	448	905	0.09	0.00	4,477		11	1
Gas Station	7	26	742	147	0.00	0.00			5	4
Jewellery	15	50	-	12,500	0.50	0.00	-		2	4
Newspaper Stand	29	4	2,525	-	0.38	0.00	4,208		8	1
Other Business	11	36	1,001	391	0.14	0.09	6,384	4,010	59	45
Pharmacy	16	10	471	586	0.18	0.11	2,122	4,782	88	476
Phone Center	10	7	1,833	900	0.00	0.00			3	2
Postal Office	25	10	290	5,291	0.29	0.20	724	21,164	7	5
Restaurant	36	21	431	1,108	0.00	0.00			7	5
Supermarket	30	17	692	853	0.15	0.10	3,945	7,313	67	134
Tobacco Shop	7	6	1,229	1,180	0.03	0.00	36,857		31	5
Video Rental	6	8	170	138	0.07	0.10	2,296	1,244	29	20

Notes: VoP stands for the value of production, and is equal to $E(Y)(1-p)/p$.

Age of Workers

We now turn our attention from firm level decision and productivity to the micro-relationship between worker characteristics and firm performance. Figure 2.6 shows the distribution of age for the robbers represented in the in the prison data. The prison shows the age of first, current, and last incarceration. All distributions are bell-shaped, and while there is considerable heaping at multiples of 5, for the police data–which is not surprising given that the age of robbers is based on victims' reports.

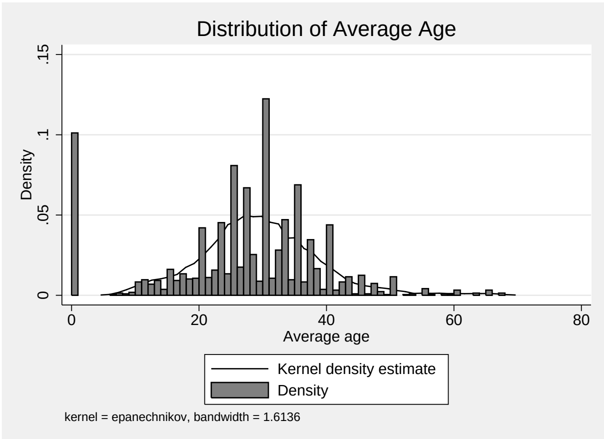

Figure 3.4: Densities of Age in Police (left) and Prison Data (right)

Notes: The age variable in the police data is based on victims reports and on the evidence from photographic footage. For 10 percent of the robberies there is no information on age (the spike at 0).

On average, robbers are younger than legal workers, with the plurality of robbers being roughly 30 years old, compared to 50 to 54 years old in the legal labor force. In the legal sector, there is a well-established, roughly log linear relationship between experience and productivity (Buchinsky et al., 2010, Shaw and Lazear, 2008). When workers first join a firm, there is a steep learning curve as workers acquire both firm and task specific human capital, and productivity increase rapidly for the first quarters of tenure (Autor and Handel, 2009, Ost, 2012). Over time, that experience-productivity curve flattens out, and eventually declines slightly if older workers are unable to, for example, adapt to changes in workplace technology or organization Ichniowski et al. (1995). Consistent with this, firms with older workers tend to be more productive, with a 10 percent increase in average worker age associated with a 0.6 percent increase in revenue per worker (Haltiwanger et al., 2011). Within a firm, there is a qualitatively similar but statistically weaker relationship between the age of employees and sales growth (Haltiwanger et al., 2011).

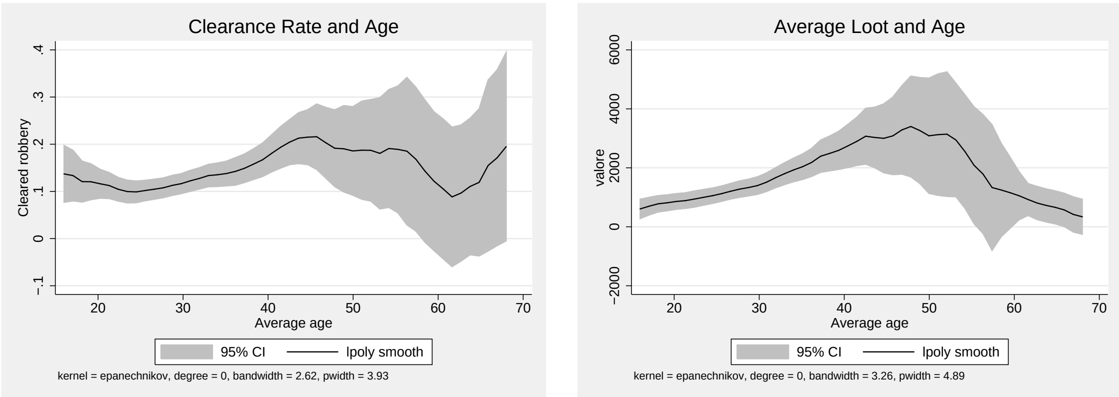

Figure 3.5: Clearance Rate and Average Loot vs. Age

Notes: Kernel-weighted local polynomial smoothing. The shaded area represents the 95 percent confidence interval.

In the illegal sector, we also find evidence that older workers are more productive, to a point. Specifically, average revenue seized increases in the average age of robbers in a group, until roughly 50 years of age. As in the legal sector, the initial increase in average revenue could be due to selection or learning; it could be the case that robbers only learn if they are high or low skilled robbers after engaging in a robbery, it is also possible that all robbers could initially be low skill, but they gain skill over time through experience.

The more dramatic decline in average loot after age 50 could also be driven by selection or skill, particularly if worker age is highly correlated with firm age. If police concentrate their resources on detecting and apprehending the most highly skilled robbery organizations, only low-skilled firms may last long enough to have older workers. Alternately, the

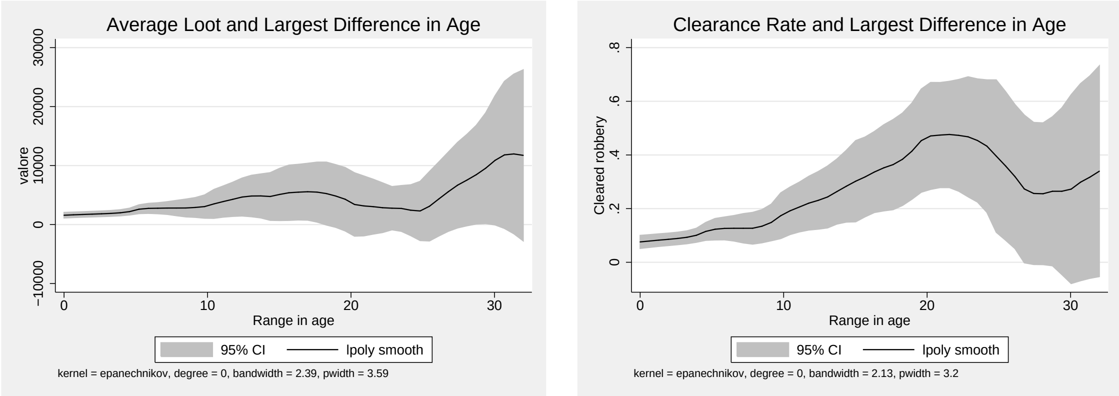

Figure 3.6: Average Loot and Clearance Rate vs. the Maximum Range in Age

Notes: Kernel-weighted local polynomial smoothing. The shaded area represents the 95 percent confidence interval.

negative relationship between worker age and revenue could be driven by human capital loss. In order to be successful, robbers must somehow coerce a person to hand over money. Physical strength is almost certainly positively correlated with illegal earnings Levitt and Venkatesh (2001), and, for most men, physical strength begins to decline after age 35 (Larsson et al., 1979).

There is a weaker relationship between worker age and legal costs. Clearance rates are relatively constant through age 35, and begin to increase slightly for workers over 40. Since clearance rates are not declining over time, this suggests that not all of the growth in average loot is due to selection out of robbery after workers learn that they are low skilled. Instead, the shallow upwards slope is consistent with police devoting more attention to larger robberies, but robbers also increasing their skill over time. After robbers age past 55, the clearance rate falls, but not nearly as sharply as the average revenue the robbers are able to capture. This is not particularly surprising, given that physical strength should not affect a robber's ability to evade the police as much as it affects the robber's ability to threaten victims. While noisy, the dip in clearance rates after 55 could be the result of police optimally choosing to no devote resources to older robbers who capture less loot.

Illegal Firms and Technology

All else equal, younger robbers may be able to extract more loot from victims, but older robbers can increase their coercive power by carrying a weapon. Indeed, robbers in firms where the average age is over 40 are increasingly likely to use a firearm, and a robber in an older firm is 50 percent more likely to use a firearm than a robber associated with a group whose average age is 30 or less (Figure 3.7). The increased reliance on weapons by older workers is consistent with human capital and technological investment being substitutes in illegal firms. Notably, this is not a typical pattern observed in legal firms, where the industry-wide adoption of new technology is typically characterized as being driven by younger workers in new firms (Bartelsman and Doms, 2000).

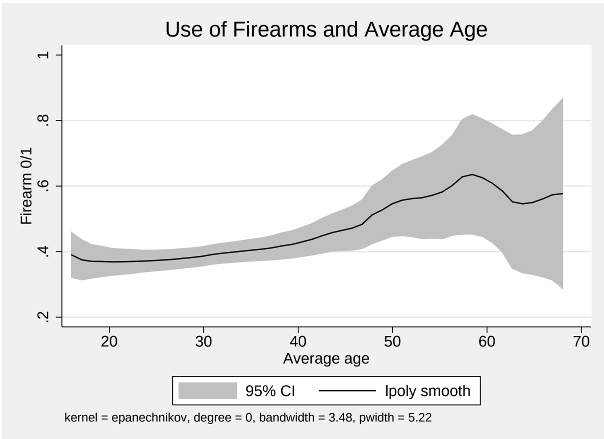

Figure 3.7: Use of Firearm and Age

Notes: Kernel-weighted local polynomial smoothing. The shaded area represents the 95 percent confidence interval.

One likely explanation for this is the difference in cost of acquiring capital across legal and illegal markets. As previously mentioned, legal firms typically have access to banks, or other creditors, from whom they can borrow money. A profit maximizing firm, even a young or small firm, will therefore adopt new technology as long as the interest demanded by the lender is lower than the firm's expected return on the technological capital investment. Illegal firms typically do not have access to functioning credit markets, making new technology more costly to acquire, as robbers must self finance any investment in weapons, or pay high interest rates on informal loans. This lack of external financing is particularly important to the extent that most crime-guns are acquired through informal channels. Young robbers who lack social ties to other market participants will pay higher prices for black market weapons than older, more connected, robbers Venkatesh (2006). Finally, anecdotal evidence suggests that there may be a psychic cost to purchasing a gun, in that a robber is admitting to himself that he is, in fact, a criminal who does not have any legal or legitimate means of supporting himself.

Of course, the argument that weapons are a substitute for human capital only makes sense if weapon carrying actually does increase revenue. Table 3.6, which summarizes the components of firm productivity by the most "serious" weapon used, suggests that this is the case. On average, firms that use firearms in the commission of robberies earn almost twice as much revenue per haul (€2222) as firms that do not use weapons (€1355). Robbers that use firearms are also less likely to be arrested than average, with in roughly 1 out of every 9 robberies resulting in a worker being caught by the police.

Table 3.6: Productivity of Firms by Types of Weapons Used

	Average Loot		Clearance Rate		Expected Loot	VoP	
Type of Weapon	Mean	Std. Dev.	Mean	Std. Dev.			Freq.
Firearm	2222	6,800	0.110	0.313	1,977	17,977	891
Knife	983	3,882	0.093	0.291	892	9,593	538
Makeshift (Improper)	1807	5,708	0.173	0.379	1,494	8,630	387
None	1355	3,827	0.179	0.385	1,113	6,233	84
Alleged	857	2,279	0.135	0.343	741	5,508	104
N.A.	743	2,515	0.299	0.459			161
Total	1631	5,494	0.137	0.344	1,407	10,278	2,165

Notes: The value of production is equal to $E(Y)(1-p)/p$.

Other types of weapons do not appear to substantively increase revenue. The lowest average loot is found in the group of robberies where the type of weapon is only alleged, and at least one person in these groups is arrested in 1 out of every 6 cases. Robbers who use knives are the least likely to be caught, potentially because of their ability to easily hide or dispose of the smaller weapon.

Using the revenue and clearance rates to infer firm productivity, workers in firms with guns are by far the most profitable, and workers would require a €18,000 per year payout to be deterred. Workers in firms with alleged weapons only have the lowest foregone earnings if caught, implying that workers who threaten, but do not actually display, weapon use are not particularly skilled.

Similar patterns emerge when we focus on multi-person firms, who can hold different types of weapons, potentially allowing for more specialization in tasks across people. Groups of robbers who use at least one gun earn the most loot per person on average, €2631, and appear to be the most productive, with a disutility of prison of at least €21,500 needed to deter them. Illegal firms with access to firearms are the most productive by far.

Table 3.7: Productivity of Firms by Weapon Holdings

	Average Loot		Clearance Rate		Expected Loot	VoP	
Joint holdings:	Mean	Std. Dev.	Mean	Std. Dev.			Freq.
At least one firearm	2631	7873	0.109	0.312	2,345	21,537	496
At least one knife, but no firearm	1225	5900	0.070	0.255	1,140	16,364	201
None	1989	5158	0.143	0.354	1,704	11,931	42
Other combinations	1598	4971	0.122	0.328	1,403	11,486	303
Total	2045	6726	0.107	0.309	1,827	17,150	1042

Notes: The value of production is equal to $E(Y)(1-p)/p$.

The return to using knives in a robbery is larger in multi-person firms than for the self employed. When the most threatening robber brandishes a knife, average loot captured was less than €1000, and the implied value of the firm's production per worker was roughly equivalent to the productivity of unarmed robbers, or robbers who used a makeshift weapon like a baseball bat. When used in conjunction with an alleged or makeshift weapon, however, knives appear to be much more useful. Groups of robbers that use at least one knife capture €1225 in loot per person, and also appear to be very effective at evading capture. This low cost of engaging in robbery means that substantially more skilled robbers work in these groups than in groups with other, non-firearm, technologies.

Informal Connections and Nationality

Another dimension that differentiates workers, and has received a large amount of attention from economists, is nationality. In the legal sector, native or local workers are often found to have better job search outcomes. Classic explanations for way local workers have the better labor market outcomes include existing social networks allowing local workers to identify better job opportunities (Montgomery, 1991), and that local workers may also have credentials, such as educational degrees or certificates, that are more familiar to local employers Ferrer and Riddell (2008). At an individual level, both of these factors will tend to lower the expected legal labor market returns for non-natives, potentially increasing the relative returns to criminal behavior.

At the same time, in the illegal sector, non-natives may also be at a disadvantage. To the extent that non-natives are less familiar with an area, they may have less information about the existence and quality of local criminal opportunities. Non-natives may also face higher cost of punishment if convicted criminal are deported, as is the case in Italy and the US. It is therefore theoretically ambiguous whether or not non-natives will engage in individual crime at a higher rate than natives.

At the group level, social networks are almost surely more important in the illegal sector than they are in legal work. As previously discussed, illegality increases monitoring costs for the employer, and robbers cannot sue each other for breach of contract if one fails to perform his agreed upon task. In the absence of formal contract enforcement, social ties can be used to create informal incentives for all parties to honor agreements, lowering transaction costs for all involved. Venkatesh (2006) offers a striking example of this in Chicago, where the in-kind cost of a back-alley oil change for neighborhood residents was lower than the cash payment required of out-of-town customers. Groups with a shared ethnicity may also be better able to coordinate and plan robberies, and as a result be able to generate more revenue than ethnically diverse groups, ceteris paribus. In a cross sectional sense, of course, these transaction costs may mean that multi-ethnic groups that do form may, on average, be more productive than homogenous groups.

Groups of non-natives may also have a comparative advantage in avoiding police detection relative to native groups, particularly if non-natives are able to communicate in a language that the police do not understand (Reuter, 2004). Witnesses that share the nationality of non-native robbers may also be less likely to cooperate with the police, making these incidents harder to clear Skogan (1984). However, just as local workers may have better signals about the location of criminal opportunities, they might also have better knowledge of the strengths and weaknesses of local detectives.

The data presented in table 3.8 suggests that illegal firms that only employ Italians are able to generate higher revenue than foreign firms. This is consistent with local workers being more aware of criminal opportunities. The apparently enhanced ability of Italians to avoid detection relative to firms with no Italian workers (17 percent arrest rate vs 13 percent), suggests that any ethnicity-based underreporting of crime, or potentially protective language differences are outweighed by better information about how to evade police.

However, we also observe that, on average, multi-ethnic groups are able to capture significantly more revenue than single-ethnic groups, and are also better able to avoid detection by police, which does suggest that there are large costs associated with the formation of these groups. Notably, multi-ethnic groups who have at least one Italian perform no better than groups without any native workers. Panel analysis of firm productivity may shed more light on this surprising result, which suggests that costs associated with coordinating multi-ethnic groups are quite high.

Table 3.8: Nationality

	Average Loot			Clearance Rate			Expected Loot			Value of Production		
	No Italians	Some Italians	Total	No Italians	Some Italians	Total	No Italians	Some Italians	Total	No Italians	Some Italians	Total
Same nationality	1,678	2,524	2,351	0.049	0.116	0.102	1,595	2,231	2,110	32,358	19,208	20,594
	5,112	8,311	7,768	0.217	0.321	0.303						
	142	551	693	142	551	693	142	551	693	142	551	693
Different nationality	1,459	1,315	1,333	0.077	0.135	0.127	1,347	1,138	1,164	17,513	8,450	9,158
	2,745	3,514	3,420	0.270	0.342	0.334						
	39	260	299	39	260	299	**39**	**260**	**299**	**39**	**260**	**299**
Total	1,631	2,136	2,044	0.055	0.122	0.110	1,541	1,876	1,820	27,886	15,365	16,559
	4,698	7,153	6,773	0.229	0.328	0.313						
	181	811	992	181	811	992	181	811	992	181	811	992

3.4 Parametric Evidence on Productivity

In equilibrium, the value of any criminal firm is based on an interaction between firm characteristics, law enforcement, victims, and the criminal law. In this section, we will estimate the relationship between firm productivity and firm decisions simultaneously in a multivariate setting. In addition for allowing, say, firm size and weapon choice to be correlated, we will also allow illegal firms to vary in unobserved ability, although of course we must assume that this unobserved ability is unidimensional and constant over time.

As in section 3.2, we will use a log-linear model to estimate the relationship between firm characteristics (x_{it}) and revenue ($\widehat{Y_{it}}$), where $\log \widehat{Y_{it}} = x_{it}'\beta^Y + \mu_i$. In this case, μ_i represents the individual gang-specific ability measures. The likelihood of arrest is going to be modelled using a logit with the individual fixed effects estimated from the haul regressions $p(x) = \frac{exp(x'\beta^p + \widehat{\mu}_i)}{1 - exp(x'\beta^p + \widehat{\mu}_i)}$ and without $p(x) = \frac{exp(x'\beta^p)}{1 - exp(x'\beta^p)}$.

Using the estimated values from each regression, it is straightforward to estimate the conditional relationship between any one component of x_{it} and underlying productivity, as

$$\frac{\partial \log D}{\partial x} = \beta_x^Y - \beta_x^p, \tag{3.2}$$

It is important to highlight that, when using a specification in logs, we must exclude observations for which the haul is equal to zero, which occurs in 19 percent of the robberies, not a negligible fraction. We do two things to take this into account. First, we simply assume that unsuccessful robberies are purely do to random chance, and predict profitability for firms with no hauls using the estimated model parameters.

However, to the extent that the relationship between firm characteristics and outcomes is different for groups that are occasionally unsuccessful, our predicted values may be biased. We therefore also model the expectations using a linear model $\frac{\widehat{Y_{it}}}{\bar{Y_{it}}} = x_{it}'\beta^Y + \mu_i$, where the coefficients can still be interpret as semi-elasticities $\partial \log \widehat{Y} / \partial x$. Because of the two-step estimation procedure, as predicted fixed effects are used in the logit regression, and in order to test the significance of the difference between the coefficients from the log-linear and linear model, we compute non-parametric clustered bootstrap estimates of the standard errors.

3.4.1 The Regression Results

The Loot

Table 3.9 presents the coefficients of a regression of the per-capita haul on several variables x that measure the modus operandi of the criminal gangs. In the first two columns the dependent variable is the log of the per-capita haul, while in the last two columns the dependent variable is the per-capita haul divided by the average per-capita haul. This way all coefficients can be interpreted as semi-elasticities. The difference in sample size between the two models is due to the 20 percent of robberies where the robbers fail to secure any loot. Columns 2 and 4 control for individual firm fixed effects, reducing concerns that unobserved heterogeneity in ability might be driving the results.

The choice of which business to target has an effect on the haul. Excluding business that are not banks, supermarkets, or pharmacies, robbing a bank, increases the haul by 197 percent without fixed effects, and 180 percent with fixed effects - this is significant at the 1 percent level. By contrast, controlling for group of robbers fixed effects robbing a pharmacy or a supermarket has no effect on the haul.

The weapon used during the robbery also makes a difference (the excluded category is no weapon). Using a firearm increases the haul by about 60 percent; this effect decreases to about 20 percent when fixed effects are used. Using levels instead of logs the effect is considerably larger: 93 percent without fixed effects, and 137 percent with. Such differences between logs and levels are driven by the 20 percent of robberies where no money has been secured.

By comparison, a cutting weapon like a knife has no effect on the log-haul, and 30 and 70 percent effect on the relative haul; the remaining weapons, like makeshift weapons (such as a baseball bat) or alleged weapons show no relationship with the haul.

Another area of interest is the composition of the group of robbers. When the size of the group increases by one robber, the per-capita haul decreases by between 15 percent (log) and 52 percent (relative haul with fixed effects). What this is showing is that the average per-capita haul exhibits decreasing returns to scale. But later we are going to see that there is another reason for adding partners in a crime.

When the robbers in a group are of different nationalities, or add robbers of different nationalities (when fixed effects are added to the regression) this reduces the average haul by between 10 and 60 percent. What might be happening is that cultural diversity might weaken the bonds between robbers and reduce their productivity.

We control for average age, as well as for the range of age and their demeaned square value ($(x - \overline{x})^2$). Both variables are not associated with the haul, especially once we control for firm effects.

The location of the robbery within the city of Milan is related to the haul as well. When the robbery occurs in the Western area, this decreases the haul by between 15 percent and 26 percent. A target in the north-eastern area decreases the haul by 27.4 percent when fixed effects are used.

Our last group of explanatory variables involves the time of day at which a robbery occurs. Robberies that take place in the afternoon and in the evening capture larger hauls, even when we focus only on within-firm variation. In terms of loot the morning robberies look like the robberies in the night.

The Risk

But the money secured is only the first dimension of productivity, risk being the second. Table 3.10 presents how the clearance rate of a robbery is related to characteristics of the

Table 3.9: Per-capita Haul Regressions

	(1)	(2)	(3)	(4)
	log-Haul		Haul/Average Haul	
Bank	1.969***	1.802***	3.299***	3.779***
	(0.184)	(0.358)	(0.620)	(1.423)
Pharmacy	0.144	0.142	-0.321***	-0.307
	(0.092)	(0.172)	(0.118)	(0.252)
Supermarket	0.195*	0.096	-0.411**	-0.263
	(0.108)	(0.164)	(0.172)	(0.200)
Firearm	0.608***	0.199*	0.931***	1.370***
	(0.129)	(0.114)	(0.208)	(0.520)
Cutting weapon	0.169	0.009	0.287*	0.694*
	(0.121)	(0.108)	(0.162)	(0.378)
Makeshift	0.111	-0.067	0.150	0.424
	(0.128)	(0.121)	(0.197)	(0.337)
Alleged weapon	0.109	-0.006	0.055	0.468
	(0.193)	(0.154)	(0.193)	(0.390)
Number of robbers	-0.136*	-0.166	0.056	-0.539*
	(0.069)	(0.102)	(0.130)	(0.316)
With different nationalities	-0.126	-0.123	-0.787***	-0.623**
	(0.117)	(0.117)	(0.251)	(0.263)
With Italians	-0.295***	-0.067	-0.206	0.102
	(0.101)	(0.124)	(0.178)	(0.196)
Average age	-0.001	0.010*	0.011	0.014
	(0.005)	(0.005)	(0.010)	(0.019)
Average age squared	-0.000	0.000	-0.001*	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Range in age	0.042**	0.019	0.097	-0.054
	(0.020)	(0.023)	(0.071)	(0.087)
Range in age squared	-0.002	0.000	-0.002	0.008
	(0.001)	(0.001)	(0.003)	(0.007)
Unknown age	0.160	0.030	0.695*	0.545
	(0.184)	(0.165)	(0.416)	(0.456)
Western area	-0.141*	-0.255**	0.008	-0.246
	(0.077)	(0.100)	(0.145)	(0.227)
North-eastern area	-0.003	-0.269**	0.072	-0.306
	(0.100)	(0.129)	(0.201)	(0.270)
Morning	0.108	-0.176	0.289	-0.216
	(0.216)	(0.244)	(0.297)	(0.285)
Afternoon	0.176	0.009	0.468**	0.430*
	(0.198)	(0.221)	(0.197)	(0.249)
Evening	0.210	-0.032	0.396**	0.385
	(0.204)	(0.238)	(0.201)	(0.240)
Fixed effect	no	yes	no	yes
Observations	1,749	1,749	2,165	2,165
R-squared	0.209	0.107	0.145	0.080
Number of Firms	729	729	907	907

Notes: All regressions control also for year, day of the week, fixed effects, and closing time dummies. Standard errors in parentheses (clustered by individual firm): *** p<0.01, ** p<0.05, * p<0.1.

crime. The first column does not include fixed effects. Column (2) uses a measure of fixed effects using the log; column (3) uses the fixed effect estimated in levels.

The first group of independent variables describes the type of business targeted. When the target is a bank, this increases the log odds that the robbers have of being apprehended by 66 percent. The increase is 70 percent with log fixed effects and 59 percent with level fixed effects (fixed-effect coefficients are reported in this order from this point on). This effect is the largest of all the categories for the type of business targeted. When the target is a pharmacy or a supermarket, the changes in log odds are not significantly different from zero.

The second group of variables describes the type of weapon used in the robbery. When the weapon is a firearm, this decreases the log odds of being apprehended by more than 100 percent, no matter the model used. Cutting weapons are associated with even larger negative changes in risk; a makeshift weapon decreases the log odds by about 70 percent, while an alleged one decreases the log odds by about 100 percent.

A third group of variables describes the composition of firms. When the number of robbers increases by one, we observe a large reduction in log odds (-55 percent). When the robbers have different nationalities they are more likely to be apprehended, but the effects is not statistically significant. When the group includes Italians, this slightly decreases the log odds of decreases the log odds of apprehension, but again, statistically speaking the change is not distinguishable from zero.

Variables that describe the ages in a group of robbers constitute the fourth set. While the average group age has almost no predictive power with respect to risk, larger ranges of age are associated with large reductions in the log odds of apprehension, -12 percent for each additional age difference between the oldest and the youngest robber. Such an effect might though be driven by dynamic considerations if older robbers train younger ones.

The location of the crime matters as well. When the robbery occurs in the western area, the log odds of apprehension decrease by 30 percent. A location in the north-eastern area decreases the log odds of apprehension by 26 percent. Though in the previous regressions we saw that this decrease is perfectly compensated with lower average hauls, which is something we are going to discuss more deeply in the next section.

The last group of explanatory variables describes the time of day the robbery took place. When it occurs in the morning, afternoon and evening the decreases in the log odds of apprehension is equal to 30, 32 and 55 percent.

The next section is going to combine the coefficients on haul and risk to estimate how the variables are associated with the value of criminal firms.

3.4.2 The Parametric Estimates of the Value of Criminal Firms

Given the estimates from Table 3.9 and 3.10 as well as Eq.3.1 the value of production can be rewritten as:

$$\widehat{D}_{i,t} = \frac{\exp(\widehat{\mu}_i + x'_{i,t}\widehat{\beta}^Y + 1/2\widehat{\sigma}_\epsilon{}^2)}{\exp(\widehat{\alpha}\widehat{\mu}_i + x'_{i,t}\widehat{\beta}^p)}, \tag{3.3}$$

when we estimate the log-haul, and

$$\widetilde{D}_{i,t} = \frac{\overline{y}(\widetilde{\mu}_i + x'_{i,t}\widetilde{\beta}^Y)}{\exp(\widetilde{\alpha}\widetilde{\mu}_i + x'_{i,t}\widetilde{\beta}^p)}, \tag{3.4}$$

when we estimate the relative haul $y_i/\overline{y}$. Notice that μ_i represents the firm specific fixed effect that we identify from the haul regression and later insert in the logistic regression, allowing it to linearly influence the log-odds. When we don't include the fixed effects $\mu_i = 0$. To recover the expected value of the haul in the log-haul regression we also have to correct for the fact that the average of a log is not equal to the log of average. Thus we added half of the estimated variance $\widehat{\sigma_\epsilon}^2$, as for log-normal random variables.

Figures 3.2 and 3.3 that we displayed in Section 3.3, showed the densities of $\widehat{D}$ and $\widetilde{D}$. The mean value of production ranges between €12,500, without fixed effects, to €25,000 with fixed effects (Table 3.11) despite the fact that the estimate based lo the linear haul model with fixed effects has about twenty percent of the data displaying negative values of production (see the cumulative distribution functions in Figure 3.8). Most of the variability of the estimated values of production is between criminal groups, as opposed to within groups over time, which is comforting given that firms do not operate for many years.

These estimates are smaller than the ones estimated in Mastrobuoni (2011). One possible explanation for this is the fact that the robberies included in Mastrobuoni (2011) are bank robberies, which we are going to see next lead to estimated values that are more than twice the overall estimates. But an additional reason might lie in the different identification strategy. Mastrobuoni (2011) estimates the return to each additional minute spent inside a bank during a robbery, which is not our focus.

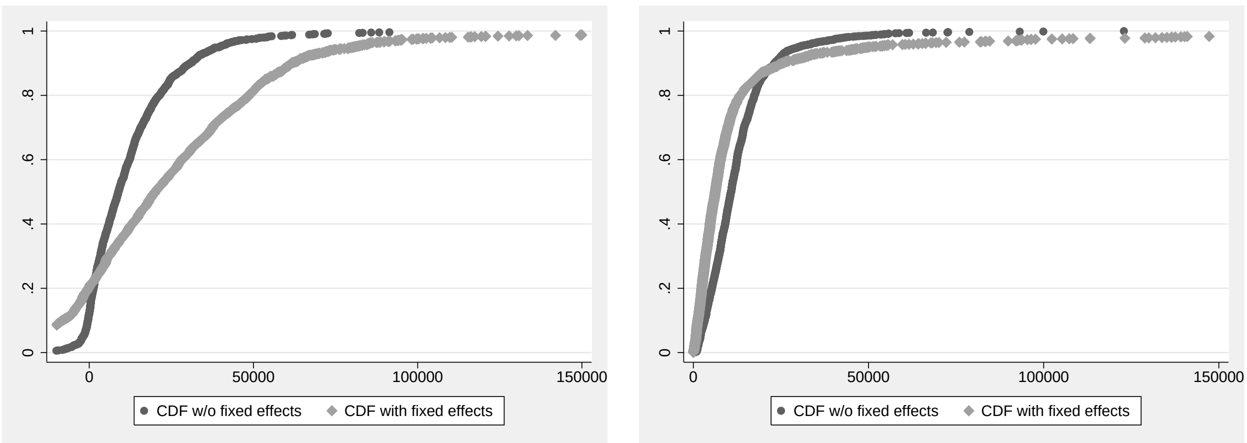

Figure 3.8: CDF of Foregone Earnings Estimated in Levels (left) and Logs (right)

Table 3.10: Logit Regressions of the Likelihood of Arrest

	(1)	(2)	(3)
		Cleared robbery	
Bank	0.664***	0.707***	0.589**
	(0.238)	(0.240)	(0.243)
		0.266	0.269
Pharmacy	0.089	0.115	0.097
	(0.174)	(0.175)	(0.174)
		0.200	0.194
Supermarket	0.115	0.148	0.106
	(0.219)	(0.220)	(0.219)
		0.248	0.250
Firearm	-1.147***	-1.088***	-1.199***
	(0.194)	(0.196)	(0.196)
		0.205	0.202
Cutting weapon	-1.297***	-1.282***	-1.350***
	(0.220)	(0.221)	(0.221)
		0.223	0.224
Makeshift	-0.696***	-0.669***	-0.728***
	(0.214)	(0.214)	(0.215)
		0.225	0.214
Alleged weapon	-0.959***	-0.942***	-0.997***
	(0.336)	(0.337)	(0.337)
		0.363	0.357
Number of robbers	-0.564***	-0.548***	-0.490***
	(0.135)	(0.134)	(0.137)
		0.174	0.162
With different nationalities	0.094	0.081	0.081
	(0.247)	(0.248)	(0.248)
		0.256	0.253
With Italians	-0.058	-0.083	-0.075
	(0.179)	(0.180)	(0.180)
		0.162	0.167
Average age	-0.011	-0.013	-0.011
	(0.009)	(0.009)	(0.009)
		0.012	0.011
Average age squared	0.001*	0.001	0.001**
	(0.000)	(0.000)	(0.000)
		0.000	0.000
Range in age	0.118***	0.120***	0.127***
	(0.035)	(0.034)	(0.035)
		0.040	0.041
Range in age squared	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
		0.001	0.001
Unknown age	-0.033	-0.019	-0.025
	(0.373)	(0.372)	(0.372)
		0.601	0.574
Western area	-0.299**	-0.284*	-0.272*
	(0.150)	(0.150)	(0.151)
		0.143	0.150
North-eastern area	-0.288	-0.258	-0.259
	(0.179)	(0.180)	(0.180)
		0.186	0.189
Morning	-0.317	-0.287	-0.292
	(0.368)	(0.369)	(0.369)
		0.372	0.377
Afternoon	-0.325	-0.311	-0.333
	(0.356)	(0.357)	(0.356)
		0.356	0.372
Evening	-0.540	-0.513	-0.552
	(0.379)	(0.379)	(0.379)
		0.380	0.407
Fixed effect		-0.186***	-0.100**
		(0.069)	(0.040)
		0.068	0.062
Observations	2,165	2,165	2,165

Notes: All regressions control also for year, day of the week, fixed effects, and closing time dummies. Standard errors in parentheses (clustered by individual firm): *** p<0.01, ** p<0.05, * p<0.1. The bootstrapped standard errors (clustered by individual firm) that take the first step sampling variation into account for the fixed effects are shown below.

Table 3.11: Mean and Standard Deviation of D

		Mean	Std. Dev.
$\widehat{D}$:			
Log-linear	overall	12,744	10,721
	between		9,349
	within		6,595
Log-linear with fixed effects	overall	16,579	65,108
	between		91,743
	within		18,640
$\widetilde{D}$:			
Linear	overall	12,567	15,740
	between		14,084
	within		9,715
Linear with fixed effects	overall	25,028	46,753
	between		52,982
	within		22,753

3.4.3 Policy Implications Based on Marginal Changes

As argued before, criminals, victims, and law enforcement are constantly playing a complex game. Criminal firms choose their targets to maximize their profits, victims try to decrease their attractiveness by investing in security devices, and law enforcement tries to be as efficient as possible given the limited resources that are available.

A result of these varying tradeoffs means that, in equilibrium, certain non-arbitrage conditions should translate into estimated marginal differences in Eq. 3.2 that are zero with respect to certain variables. Table 3.12 and 3.13 report such marginal differences for the two models of hail (log and level) dividing the variables into four groups: i) targeted victims (focusing on just the three most popular), ii) weapons and size, iii) individual characteristics, and iv) policing variables.

Starting with the victims, one should expect that in equilibrium robbers should be almost indifferent about which business to target. If there was one preferred business that lead to larger values of production, in a world without informational frictions and perfectly rational robbers, such a business would attract most robbers. Attracting so many robbers, the business would have a strong incentive to invest in security devices.

Table 3.12 and 3.13 show that banks represent more attractive business than the rest. This might in part depend on the fact that banks are typically insured against robberies, introducing concerns of moral hazard.

Table 3.12: Marginal Effects Based on the Log-Model

	Marginal effects without fixed effects					Marginal effects with fixed effects				
	β^Y	β^p	Δ	SD	t-stat	β^Y	β^p	Δ	SD	t-stat
Targeted victims										
Bank	1.97	0.67	1.30	0.34	3.77	1.80	0.71	1.09	0.47	2.33
Pharmacy	0.14	0.09	0.06	0.22	0.26	0.14	0.11	0.03	0.26	0.11
Supermarket	0.19	0.08	0.12	0.26	0.44	0.10	0.11	-0.02	0.28	-0.06
Weapons and Size										
Firearm	0.61	-1.13	1.74	0.25	7.11	0.20	-1.08	1.27	0.25	5.19
Cutting weapon	0.17	-1.33	1.49	0.26	5.79	0.01	-1.31	1.32	0.26	5.11
Makeshift	0.11	-0.70	0.81	0.27	3.01	-0.07	-0.67	0.61	0.27	2.28
Alleged weapon	0.11	-0.96	1.07	0.43	2.48	-0.01	-0.94	0.93	0.41	2.26
Number of robbers	-0.14	-0.57	0.43	0.19	2.24	-0.17	-0.55	0.39	0.20	1.92
Individual characteristics										
With different nationalities	-0.13	0.09	-0.22	0.29	-0.75	-0.12	0.08	-0.20	0.29	-0.70
With Italians	-0.29	-0.06	-0.23	0.20	-1.18	-0.07	-0.09	0.02	0.23	0.09
Average age	0.00	-0.01	0.01	0.01	0.75	0.01	-0.01	0.02	0.01	1.74
Age range	0.04	0.12	-0.08	0.05	-1.58	0.02	0.12	-0.10	0.05	-1.91
Unknown age	0.16	-0.02	0.18	0.50	0.36	0.03	-0.01	0.04	0.48	0.08
Firm fixed effect						1.00	-0.18	1.18	0.07	17.32
Policing variables										
Western area	-0.14	-0.30	0.16	0.16	0.98	-0.25	-0.29	0.03	0.19	0.16
North-eastern area	0.00	-0.34	0.34	0.23	1.47	-0.27	-0.31	0.04	0.25	0.17
Morning	0.11	-0.32	0.42	0.45	0.94	-0.18	-0.29	0.11	0.46	0.24
Afternoon	0.18	-0.33	0.51	0.43	1.19	0.01	-0.32	0.33	0.44	0.75
Evening	0.21	-0.49	0.70	0.48	1.45	-0.03	-0.46	0.43	0.50	0.85

Notes: The standard errors and the t-statistics are bootstrapped at the firm level using 1000 replications.

Table 3.13: Marginal Effects Based on the Model in Levels

	Marginal effects without fixed effects					Marginal effects with fixed effects				
	β^Y	β^p	Δ	SD	t-stat	β^Y	β^p	Δ	SD	t-stat
Targeted victims										
Bank	3.30	0.67	2.63	0.71	3.70	3.78	0.60	3.18	1.52	2.10
Pharmacy	-0.32	0.09	-0.41	0.23	-1.78	-0.31	0.10	-0.40	0.35	-1.15
Supermarket	-0.41	0.08	-0.49	0.30	-1.62	-0.26	0.07	-0.33	0.37	-0.91
Weapons and Size										
Firearm	0.93	-1.13	2.07	0.30	6.83	1.37	-1.19	2.55	0.62	4.11
Cutting weapon	0.29	-1.33	1.61	0.28	5.70	0.69	-1.38	2.07	0.48	4.28
Makeshift	0.15	-0.70	0.85	0.30	2.84	0.42	-0.73	1.15	0.44	2.61
Alleged weapon	0.05	-0.96	1.01	0.41	2.47	0.47	-0.99	1.46	0.57	2.57
Number of robbers	0.06	-0.57	0.62	0.21	2.91	-0.54	-0.49	-0.04	0.40	-0.11
Individual characteristics										
With different nationalities	-0.79	0.09	-0.88	0.34	-2.57	-0.62	0.08	-0.70	0.34	-2.04
With Italians	-0.21	-0.06	-0.14	0.26	-0.55	0.10	-0.08	0.18	0.30	0.61
Average age	0.01	-0.01	0.02	0.01	1.48	0.01	-0.01	0.03	0.03	0.99
Age range	0.10	0.12	-0.02	0.09	-0.24	-0.05	0.13	-0.18	0.10	-1.83
Unknown age	0.70	-0.02	0.72	0.63	1.13	0.55	-0.01	0.56	0.69	0.80
Firm fixed effect						1.00	-0.10	1.10	0.06	18.23
Policing variables										
Western area	0.01	-0.30	0.31	0.21	1.47	-0.25	-0.27	0.03	0.30	0.10
North-eastern area	0.07	-0.34	0.41	0.29	1.43	-0.31	-0.31	0.01	0.37	0.02
Morning	0.29	-0.32	0.60	0.47	1.30	-0.22	-0.29	0.07	0.47	0.16
Afternoon	0.47	-0.33	0.80	0.40	2.03	0.43	-0.34	0.77	0.44	1.77
Evening	0.40	-0.49	0.88	0.45	1.97	0.39	-0.50	0.88	0.46	1.94

Notes: The standard errors and the t-statistics are bootstrapped at the firm level using 1000 replications.

For the second category, we need to take into account that the use of weapons not only represent an investment but also increase the expected duration of the disruption of production. But as shown in Mastrobuoni (2011) the only weapons that lead to a 50 percent increase in severity are firearms, while the estimated changes in the value of production when firearms are used are in excess of 50 percent (127 to 255 percent depending on the model). Cutting weapons are also associated with considerably larger values of production. What this means is that there judges might consider assigning longer sentences to robbers who use any weapons, instead of only penalizing firearm use.

The third set of variables analyze individual characteristics like nationality, and age. Apart from the range of age, no other variables are consistently associated with significant differences in the value of illegal production. The negative relationship between age range and productivity is consistent with our parametric analysis of ethnicity- workers who are not familiar with each other may simply have a hard time coordinating.

We find no evidence that robberies in any one area are more productive than robberies in another area, despite the large geographic differences in risk and average haul. This is consistent with the equilibrium prediction such differences, when they exist, are arbitraged away. There is some evidence that afternoon and evening robberies are more productive than those that happen at night, but such an effect is more likely to be driven by unprofessional robbers that operate at night, when the police are quite efficient given lower levels of traffic and (overall) lower levels of criminal activity.

Data on trials against bank robbers allows us to judge how the productivity differentials we observed across *modus operandi* maps into differential sentences.[3] Given that sentence enhancements are proportional to the baseline sentences we regress log-sentences on the *modus operandi* of robbers. While using firearms or a cutting weapon leads to longer sentences (+37 and +19 percent), such enhancements are considerably lower than the observed difference in productivity (+255 and +200 percent).

[3]The estimates in Table 3.14 are based on trials from the *Torino* court of justice.

Robbers who operated in a group receive slightly larger sentences (8 percent) but such difference is not significantly different from 0, while there is a 75 percent chance that productivity increases by 40 percent when more robbers are participating.

Table 3.14: Determinants of Log-Sentences

	(1)	(2)
	Log-Sentence Length	
Firearms	0.38***	0.37***
	(0.120)	(0.136)
Cutting Weapons	0.14	0.19**
	(0.091)	(0.092)
Masked	-0.00	-0.02
	(0.070)	(0.066)
Group robbery	0.08	0.08
	(0.075)	(0.070)
Number of robberies	0.04***	0.04***
	(0.010)	(0.012)
Recidivist	-0.01	-0.03
	(0.090)	(0.084)
Hostages		-0.07
		(0.117)
Total haul		-0.00
		(0.000)
Plea bargain		-0.30***
		(0.084)
Year	0.00	0.01
	(0.005)	(0.005)
Observations	94	94
R-squared	0.305	0.410

Notes: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

3.5 Conclusions

In 1968, Gary Becker pointed out that there is no separate law of "criminal behavior," where some people are motivated by a particular deviant philosophy or creed that leads them to commit crime. Rather, people respond to incentives in a way that maximizes the present value of their utility. Variation in behavior across individuals can, to a large extent, be explained by variation in the incentive structure that individual face, rather than fundamental differences in people. Using detailed data from Milan, we have shown that "criminal careers" are strikingly similar to legal careers.

Our analysis of prison data shows that, just as the majority of people who suffer job disruptions eventually return to work, a large fraction of the criminal population does not desist from crime after one period of incarceration. Indeed, the younger a person is when they are first incarcerated, the more likely they are to return to the criminal labor market. As in the legal labor market, mobility declines with experience, and we observe more switching between criminal industries among less experienced criminals. Prolific offenders, who in the past have had no trouble locating an acceptable criminal opportunity, either because of a low criminal reservation wage or a high underlying level of productivity, will return to crime faster.

The framework of labor economics and human capital accumulation clarifies the policy implications of certain statistical associations. Longer sentences, which put inexperienced criminals in close quarters with a concentrated pool of offenders, may have a perverse impact on criminal outcomes. Longer periods of incarceration are essentially longer periods of forced unemployment, during which time a worker becomes increasingly less likely to return to work. At the same time, incarceration puts criminals on contact with each other, potentially allowing for the development of networks, or other criminal capital, that would facilitate participation in future criminal opportunities. When criminals are still early in their career, this enhancement effect appears to dominate the disruption (and deterrent) effect, and longer sentences exacerbate criminal behavior. As criminals gain experience, however, the disruption effect appears to dominate, which is consistent with diminishing returns to networking or human capital development.

The non-monotonic relationship between sentence length and recidivism suggests that criminal-history based sentence enhancements might be preferable to a "scared straight" approach that uses harsh punishments to "shock" first time offenders. Structured sentencing regimes that assign longer sentences to people with longer criminal histories are common in the United States, and include notorious "Three Strikes" laws as well as more nuanced history-based sentencing guidelines, like those used in the states of Maryland and Pennsylvania. The Netherlands also explicitly requires the repeat offenders serve longer punishments.

Italy reformed its sentencing guidelines at the end of 2005, assigning longer sentences to multiple recidivists. We find strong evidence in our data that before 2006 multiple recidivists did not receive more severe punishments and that this changed considerably with the reform.

Of course, the fact that the rate of recidivism appears to be highly correlated within individuals suggests that the size of an offender enhancement should perhaps deteriorate over time, and that the return to incarcerating older criminals is lower, since shorter job disruptions are more likely to lead to permanent exit from the legal labor market.

After establishing the dynamic nature of criminal careers, we used a unique set of police data to describe one specific criminal industry. Examining the pattern of robberies and co-offending in Milan yields a number of interesting insights. First, just as in the legal sector, there is vast heterogeneity in firm productivity. Even conditional on firm size, technology, and task specialization, there are is still a more than 110 percent difference in the implied productivity of the most successful and least successful groups. We find evidence that illegal firms are probably inefficiently small, that there is a quadratic relationship between productivity and age, and that technology can also be a substitute for physical strength. Firms the specialize in one particular type of victim, be it Banks, Supermarkets, or Pharmacies, appear to be better at extracting revenue from targets than firms which attack many types of companies, and in some cases specialization allows for firms to rob more victims in the same period of time- producing more output as well as higher quality output. Using ethnicity as a proxy for social connectivity among workers, we find that firms that employ workers with informal ties are more effective than less cohesive organizations, and that homogenous groups that are foreign appear to be the most productive. This last result, which is not consistent with traditional labor literature, is consistent with foreigners being better able to avoid detection.

The large amount of heterogeneity in productivity across firms within the robbery industry reinforces the idea that not all crimes, or all criminals, are alike. Indeed, it suggests that an optimal sentencing policy aimed at deterrence should be based on how crimes are committed, rather than simply the crime itself. While Italy currently imposes higher punishments for using firearms, the punishment cost of using a firearm is still far below the illegal return. Our results also suggest that there is scope for stricter sentence enhancements for knife use. Currently, robbers who use knives receive sentence enhancements that are one half the size of firearm enhancements. However, it appears to be the case that using a knife has almost the same return as using a gun. While adding an additional worker to a firm does not necessarily increase productivity, large groups are much better at evading detection. The current 8 percent sentence enhancement for co-offending is not nearly as large as the roughly 40 percent illegal return to an additional employee.

Of course, we are limited in our ability to generalize these findings about illegal group behavior to other types of crimes. It is possible that, say, car theft or burglary rings behave in ways that are entirely at odds with stylized facts about legal companies. The spread of predictive policing as a way of combatting crime means that similar data from other cities and for other criminal outputs will be increasingly available to researchers.

Further, researcher on criminal careers and criminal firms should not develop in parallel with labor economic literature on worker and firm mobility, but rather draw on theoretical insights from the legal sector.

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