Optimizing Criminal Behaviour and the Disutility of Prison*

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Abstract

We use rich microdata on bank robberies to estimate individual-level disutilities of imprisonment. The identification rests on the money versus apprehension trade-off that robbers face inside the bank when deciding whether to leave or collect money for an additional minute. The distribution of the disutility of prison is not degenerate, generating heterogeneity in behaviour. Our results show that unobserved heterogeneity in robber ability is important for explaining outcomes in terms of haul and arrest. Furthermore, higher ability robbers are found to have larger disutilities, suggesting that increased sentence lengths might effectively target these more harmful criminals.

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JEL classification codes: K40, K42, H11

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At least since Becker's 1968 seminal model of crime, economists have believed that criminal decisions depend on *individual* probabilistic expectations about illegal proceeds, risk of apprehension, and the consequent loss of utility associated with getting caught and punished. Empirical measures of this heterogeneity, however, are scarce, since criminals' expectations are not usually directly observable.[1] Criminal proceeds are also typically not observed,[2] and because of data limitations the probabilities of arrest and conviction are often assumed to be constant for a given crime, a given location, and a given time period.

With respect to the disutility of being imprisoned, data limitations are even more severe. Disutility is likely to depend on a variety of unobserved factors (opportunity cost of prison time, including market skills and potential legitimate earnings, aversion to prison, aversion to risk, time preferences, family relations, friendships, etc.). Yet without detailed micro-level data, most crime research has been forced to fully disregard such heterogeneity. This is unfortunate as it has been shown that disutility shapes general deterrence.[3]

The distribution of disutility is important because it impacts the efficacy of a given law enforcement policy, and thus influences the design of optimal policy.[4] For instance, heterogeneity in disutility implies that different policies may be necessary to effectively target different offenders. Individuals with large disutilities of prison are likely to be responsive to increases in the certainty or length of imprisonment. In contrast, for offenders at the low end of the distribution, policies that raise the disutility of prison directly are likely to be more effective. For example, increasing educational attainment (thereby improving labour market outcomes) for individuals at risk of offending increases the opportunity cost of offending and thus the disutility of prison (see Lochner, 2004 and Lochner and Moretti, 2004).[5]

[1]For evidence on the formation of criminals' expectations, see Lochner (2007), Hjalmarsson (2009), and Anwar and Loughran (2011).

[2]According to Witte (1980) "[n]ew data sets should also make every possible effort to obtain estimates of the expected payoff from illegal activity." Presently, very few crime datasets contain information on the value of stolen goods. Victimization surveys are an exception, but they typically focus on the victims and contain little information about criminal behaviour. The National Incident-Based Reporting System (NIBRS) is among the few data sources with some statistics about criminal proceeds.

[3]See Polinsky and Shavell (1999) for a theoretical discussion about the importance of the disutility of imprisonment, and also Lee and McCrary (2017) for some comparative statics results when changing what they call the "utility cost to incarceration."

[4]See Durlauf and Nagin (2011) for an overview on the estimated "aggregate" deterrence effect of imprisonment.

[5]More recently, using data from Norway, Bhuller *et al.* (2016) find that for criminal offenders who were not employed prior to being arrested, incarceration leads to lower rates of recidivism upon release, compared to those who were not incarcerated. The authors attribute this to programs within the prisons designed to rehabilitate, provide job training, and support re-entry into society. These programs, which

Heterogeneity in disutility is also important in the context of sentence enhancements, which increase prison sentences based on the circumstances of the offence. Sentence enhancements are typically used to discourage crimes involving more harm (e.g., more money is stolen or a firearm is used) or as a way of compensating for a lower probability of apprehension (e.g., when a mask is worn to conceal a robber's identity). An additional motivation for sentence enhancements is to target those individuals most responsive to a change in punishment, thus increasing the efficiency of law enforcement (see Becker, 1968). To a limited extent this motivation is currently incorporated in some sentencing decisions. For example, higher punishments are given for premeditated murder which is more likely to respond to a change in sanctions compared to impulsive crimes of passion. However, without a direct measure of this heterogeneity in disutility, it is not possible to take full advantage of these differences.

The main contribution of this paper is to estimate heterogeneity in the disutility of prison, and thus individual deterrence, using data on almost 5,000 individual bank robberies that happened in Italy between 2005 and 2007. Each year there are more bank robberies in Italy (approximately 3,000) than in the rest of Europe combined, with a 10% chance of victimization on average (there are about 30,000 bank branches). In the Western world only Canada has a higher risk rate, defined as the number of robberies divided by the number of bank branches.[6] By comparison, according to the Uniform Crime Statistics, the United States has a population more than five times that of Italy, but only three times as many bank robberies (Weisel, 2007).[7]

Our data come from the Italian Banking Association, which records information on the amount of seized cash and the exact duration of the robbery, as well as whether an arrest has been made (and whether it was made immediately or after some time). Managers of victimized Italian bank branches fill out a detailed survey describing the characteristics of the robbery, including information on the number of robbers, list of weapons used, time of day, number of employees and customers present, among others. In addition, the data include detailed characteristics of each branch that was robbed, including the number and type of security devices, whether a security guard was present, the location of the branch, and the typical level of cash holdings.

lead to significantly higher rates of post-release employment, effectively increase the opportunity cost of subsequent offending. Since the individuals affected were those previously unemployed, the policy targets those who are likely to have lower opportunity costs to begin with.

[6] For an international comparison of robberies see the Online Appendix O1.

[7] In the US there are around 10,000 bank robberies per year, representing more than 10% of all commercial robberies (Weisel, 2007; Federal Bureau of Investigation, 2007). See Cook, 2009, 1987, 1986, 1985, 1983 for a discussion of robberies more generally.

By looking closely at heterogeneity in strategy and behaviour, this study combines economic modelling with a unique set of detailed bank robbery data to study the interplay between criminals and criminal law. The identification of the disutility of prison rests on a trade-off faced by robbers: after selecting a bank branch, a weapon, a disguise, a team, etc. (in short, a *modus operandi*), robbers need to choose how much time to spend inside the bank collecting the money.[8] Robberies represent an ideal laboratory for these trade-offs, but there are a number of other crimes with similar intensive margins.[9]

The optimal robbery duration depends on robbers' expectations about the size of the haul, the likelihood of apprehension, and the disutility of prison if caught. Criminals with a higher expected marginal (per minute) haul, a lower expected risk of arrest (the hazard rate of arrest), or a lower disutility of prison will want to spend more time collecting money.[10]

Our rich dataset allows us to model *individual-level* expectations of criminals, controlling for many factors that might influence all of these components. Using data on realized hauls and arrests, we estimate the expected haul function and hazard of arrest. Given estimates of these two objects we can use the information on the amount of time robbers chose to stay in the bank to recover an estimate of the disutility of prison that rationalizes this choice. We can do this calculation separately for each robbery, allowing us to recover the distribution of disutility.

Since the returns to bank robbers are measured in terms of the size of the haul, our measure of the disutility of prison is the compensating variation, which measures the price an individual criminal would be willing to pay to avoid prison once arrested. We will refer to the compensating variation more informally as the disutility of prison.

A second contribution of this paper recognizes that optimal criminal policy depends not only on heterogeneity in the costs of enforcement (through heterogeneity in deterrence, as in Mookherjee and Png, 1994), but also on heterogeneity in the benefits of enforcement (through heterogeneity in criminal harmfulness, as in Polinsky and Shavell, 1992). The detailed information on robbery characteristics in our data allows us to identify which

[8]More anecdotal evidence on this trade-off can be found in Cook (2009) and Bernasco (2010).

[9]Other examples include the decision of how long to spend burglarizing or committing theft, the amount of money to embezzle, and the amount of time spent on the road as a drunk driver. In all of these examples there is a trade-off between higher rewards and higher costs that depends on the intensity of the crime.

[10]See Viscusi (1986) and Harbaugh *et al.* (2013) for other papers that empirically examine the trade-off between the risk and rewards of criminal activity. Viscusi (1986) uses individual-level data on inner-city minority youths in the United States to estimate risk premiums associated with different levels of risk of punishment. Harbaugh *et al.* (2013) use an experimental design to examine the effect on criminal activity of the rewards to crime, risk of getting caught, and the value of the punishment if caught.

characteristics are associated with more harm to banks in terms of larger hauls and lower rates of apprehension (thus increasing the chances of future robberies),[11] as well as those related to larger disutilities of prison.

While our data contain a wealth of information about each robbery, there is one characteristic of the robberies that is inherently unobserved: robber ability. Individuals with higher robber ability are likely to have larger hauls and lower arrest probabilities. Their ability might also affect the disutility of prison, for example through an increased opportunity cost of imprisonment.[12] In order to deal with unobserved heterogeneity in robber ability, we estimate the expected haul and hazard rate of arrest jointly, employing a factor model to control for unobserved ability and the correlation it generates in terms of outcomes (haul, apprehension, and robbery duration).[13]

We find that the most successful robbers in terms of hauls use weapons, wear masks, and rob banks with fewer security devices and no guards. Those who work in groups, wear masks, target banks around closing time, and target banks with no security guards and few employees, achieve lower rates of apprehension. Offenders who use a mask and target banks without security guards have higher disutilities of prison. Robber ability is also found to be a strong driver of larger hauls, lower probabilities of arrest, and larger disutilities of prison. The latter finding is consistent with higher ability offenders having a larger opportunity cost of prison.

To the best of our knowledge, there are no other papers that estimate the entire distribution of the disutility of prison, although two other papers estimate some statistic of the distribution.[14] Abrams and Rohlfs (2011) use bail postings, the amounts paid by suspects to be released while on trial, to estimate the average disutility of prison. Their estimate of the disutility is \$4,000 per year. They explain this low figure by saying that "(t)his seemingly low estimate may result in part because they pertain to a particularly poor segment of the population. Credit constraints may also affect the estimate." Our

[11] In the context of bank robberies, harm could also include violence or threats of violence.

[12] Higher robber ability could be associated with higher opportunity costs of imprisonment for two reasons. First, incarcerated individuals are not able to rob banks, the value of which depends on robbery ability. Second, to the extent that robber ability is positively (negatively) correlated with an individual's productivity in the legal sector, higher ability could increase (decrease) the opportunity cost of prison through foregone legal employment."

[13] See Anderson and Rubin (1956) and Jöreskog and Goldberger (1975) for early discussions of factor models and Heckman *et al.* (2006) for a more recent treatment in the context of risky behaviours (including crime).

[14] In spirit this paper is also related to the vast literature that estimates the value of life based on trade-offs between fatality risk and different kinds of returns, for example wage premia in the labor market (Thaler and Rosen, 1976; Viscusi, 1993), or the saving of time when speeding (Ashenfelter and Greenstone, 2004).

paper goes beyond estimating the average disutility of prison by backing out its distribution, and does not require information about, nor are the estimates affected by, credit constraints. The second paper, Reilly *et al.* (2012), uses aggregate data to estimate an average disutility of prison for British bank robbers that is larger (£33,545), corresponding to an average sentence of around 3 years. However, this estimate is also likely to be biased due to aggregation.[15]

With not just one statistic but the entire distribution of disutility at hand, our results can be used to help policy-makers design sentencing enhancements to target those characteristics associated with both more harm and larger deterrence.[16] Our finding of substantial dispersion in disutility across individuals implies heterogeneous responses to policies designed to reduce crime. Furthermore, our estimates allow us to examine the relationship between heterogeneity in disutility and heterogeneity in criminal harmfulness. The correlation between these two measures of heterogeneity is important because if more harmful crimes are committed by offenders with lower disutilities of prison, then policies targeted at these individuals will be more costly, mitigating the net social benefit. If instead the correlation goes in the other direction, then policies designed to reduce harm and increase efficiency are complementary, leading to an amplification of the benefits of enforcement.

We find that heterogeneity in robber ability generates a positive correlation between criminal harmfulness and disutility. An importance consequence of this is that policies designed to affect those with higher disutilities of prison (for example simply raising overall sentences) have the added benefit of disproportionately targeting the more harmful (higher ability) offenders.

[15] Reilly *et al.* (2012) compute an upper bound on the disutility of prison by setting the expected gains from a robbery equal to zero. Their calculation involves dividing the average haul by the average odds of arrest. However, when there is heterogeneity in the expected haul and probability of arrest, this ratio can be seriously biased, as the average ratio is not equal to the ratio of averages. If these two expectations are correlated with each other, for example due to heterogeneity in ability, then this can induce further bias.

[16] Several recent studies have estimated "average" deterrence effects by exploiting some form of random variation in sentencing (Drago *et al.*, 2009, Helland and Tabarrok, 2007, and Kessler and Levitt, 1999–although the results of the latter have been challenged by Webster *et al.*, 2006 and Raphael, 2006). However, they were forced to disregard any potential heterogeneity in the disutility of prison (e.g., due to the opportunity cost of incarceration, aversion to prison, etc.). This study exploits the individual and continuous trade-off to estimate the entire distribution of deterrence effects.

1 The Data

We have been granted access to a unique dataset that covers the universe of individual bank robberies perpetrated in Italy between 2005 and 2007.[17] Each year branch managers are required to record updated information about the characteristics of their branch (number and type of security devices, presence of a guard, etc.). In addition, after each robbery, branch managers are required to fill out a form describing specific details of the robbery (e.g., number of bank robbers, total haul, weapons used, time of day). Managers also have to record the exact duration of the robbery in minutes. All bank branches have surveillance cameras that can be used to reconstruct the duration. The vast majority of robberies are relatively short: 87% last 9 minutes or less, and over 95% are 30 minutes or less. However, there is a very long right tail. Since these much longer robberies are likely to follow a very different *modus operandi* (e.g., accessing the vault as opposed to gathering the money from the tellers), we exclude the 4.3% of robberies that last more than 30 minutes.[18] We also drop those observations with missing information on either the robbery or characteristics of the branch, leaving us with 4,969 observations out of an initial 6,098.

The distribution of robberies over time is shown in Table 1, where we separate successful (no arrest was made) from unsuccessful (an arrest was made) ones.[19] At the beginning of the robbery (time 0), the data start with 4,969 robberies that last less than 30 minutes. Two hundred ninety-two last just one minute. Of these, 20 lead to an arrest and 272 do not. The latter are labelled as successful, even if the robbers walk out of the bank empty-handed. After the first minute 4,677 robberies are left, of which 71 lead to an arrest and 1,041 terminate without an arrest during the next minute, and so on. After 10 minutes only about 5% of the initial robberies are still ongoing.

Table 2 provides summary statistics for our dataset. Overall, 6.6% of bank robberies led to an arrest.[20] The average robbery lasts 4.27 minutes and leads to a haul of approx-

[17] Online Appendix O1 shows the evolution of robberies over the last 15 years and discusses the Italian robberies in comparison to other countries, including the United States.

[18] Our results are very similar if we limit the data to robberies lasting less than 10 minutes.

[19] The data that were provided by the Italian Banking Association do not contain any information about the arrested robbers, in particular whether or not they were ultimately convicted. As a robustness check, we hand-collected data on all trials against bank robbers that ended between 2005 and 2007 in the judiciary district of Turin (the second largest city in Northern Italy). These data, described in more detail in Online Appendix O2, show that only one out of 96 robbers (covering 324 bank robberies) was acquitted. Similar data based on commercial robberies perpetrated in Milan (not just against banks) also show conviction rates that are close to one (see Mastrobuoni, 2014). Given this evidence we feel it is reasonable to treat arrests as convictions.

[20] Fifty-nine percent of these arrests are *in flagrante delicto*, during the bank robbery, while the rest

imately €16,000. Given that more than half of all bank robberies involve two or more perpetrators, the average haul per criminal is approximately equal to €8,700.

Only 15% of bank robberies involve firearms. In the United States the fraction is twice as high, possibly because weapons are more widespread. But differences in the severity of sentencing enhancements might also influence this difference. US federal guidelines impose sentences for bank robbers of up to 20 years, with an additional 5 years (25%) added when a dangerous weapon (e.g., a firearm) is used. In Italy, instead, the law (Art. 628 of the penal code) prescribes that the sentence length should range between 3 and 10 years for "simple" robberies and between 4.5 and 20 years for aggravated robberies, which are robberies in which: a weapon is used, the robber uses a disguise, a group of robbers is involved, violence is used to incapacitate a victim, or the robber belongs to an organized crime association. Thus, sentencing enhancements when weapons are used are between 50% and 100 %, at least twice as large compared to the United States. Another 70% of robbers use knives or makeshift weapons, while the remaining 15% use just threats and no weapons, typically handing a note to the teller.

As in the United States, only about 40% of all bank robbers disguise themselves when robbing a bank (this might again be a response to slightly larger sanctions for disguised offenders). Some US states and US cities have introduced similar sentencing enhancements against disguised robbers. For example, since 2007, in the city of Los Angeles, wearing a disguise during a robbery comes with an additional 25% sentencing enhancement as well as making the offender ineligible for any type of early release. In Massachusetts, masked robbers face a minimum mandatory sentence of five years in state prison.

Our data also contain information about how the perpetrators reached the bank premises. The majority of robbers reach the branch on foot (34%) or by car (20%). Another 7% reach the branch using a motorbike, while the remaining 39% of robbers are able to successfully hide their mode of transportation.

The data set is rich with information about the security devices installed in the bank. We summarize this information by counting the number of different devices that each bank employs and how many characteristics these devices have on average. For example, 92% of the banks have a security entrance, but the characteristics differ widely. Some have metal detectors, some have double doors between which people can be trapped, some have a biometric sensor, etc., while some entrances might display all these characteristics. Two-thirds of these devices might not be visible (e.g., automatic banknote distributors, banknote spotters, time-delayers, banknote tracing devices, vaults, and alarm systems)

happened after robbers exited the bank.

while the rest are visible (e.g., metal detectors, vault time-locks, and protected teller posts). On top of such devices about 8% of branches employ security guards.

The data also contain information on the number of customers and employees that were present at the time of the robbery. On average there are about 5 employees and 3 customers.

We group robberies into 4 different time-of-day intervals. More than 60% of robberies happen between 8am and noon, about 30% between noon and 3pm, and 8% around the opening time (before 8am) or right before closing time (3pm to 4pm). Robberies are also slightly more likely to happen on Friday than on other days of the week.[21]

2 A Continuous Time Model of Crime

The key insight of our model is that bank robbers face a trade-off when deciding how long to stay in the bank. By staying an extra minute, the robbers can collect more money, but they also run the risk of getting caught and sent to prison. The cost of being apprehended is a function of the disutility each individual places on going to prison. By equating the marginal benefit with the marginal cost of time spent in the bank, we can back out the unobserved disutility that robbers assign to prison.

Conditional on having chosen to rob a bank, the criminal's expected utility $V(t)$ is a function of the duration t of the bank robbery. It is also a function of the criminal's initial wealth (W), discount factor (δ), risk aversion (r), as well as the trade-off between haul and risk of apprehension, which in turn depend on ability, as well as the characteristics of the chosen bank branch, which are predetermined once he starts the robbery.[22]

The precision of the robbers' expectations about the benefits and costs of spending an additional minute inside the bank branch is likely to depend on their own experience. The Turin judiciary data show that more than two-thirds of sentenced robbers are recidivists (have already been convicted for a similar crime). On average, these recidivists are convicted for three additional bank robberies in trials taking place from 2005-2007. Moreover, more than half of the remaining one-third of robbers that have no previous convictions are sentenced for multiple robberies.[23] Thus for only about 15% of robbers, law enforcement

[21] Since bank branches are supposed to be closed during weekends we disregard the few robberies that happen on Saturday or Sunday.

[22] Harding (1990), for example, interviews almost 500 robbers and finds that most of them choose whether to use a gun rationally, considering the benefits (improvement in outcomes) and costs (increase in sanctions).

[23] In robberies against businesses in the city of Milan, the police try to identify offenders across robberies using surveillance cameras and victim reports. Based on such data, 70% of robberies are performed by

is unable to detect some previous experience, and even this level of inexperience is likely to be biased upwards given that not all criminal acts can be observed.

Based on the robber's expectations, his decision problem can be formulated as:

$$\max_t V(t) = [1 - \Pr(T_p < t)]E\left[U\left(W + Y(t), \delta\right)\right] + \Pr(T_p < t)\widetilde{U}\left(W, d, S, \delta\right), \tag{1}$$

where $Y(t)$ is the haul after t minutes, T_p is a random variable denoting the time of police arrival, and $F(t) = \Pr(T_p < t)$ represents the probability of apprehension before time t. The random variable T_p defines the two states of the world, arrest (and conviction) $T_p < t$ and no arrest $T_p \geq t$.[24] $E[U(W + Y(t), \delta)]$ is the expected present-discounted utility from no arrest and an uncertain haul after t minutes, where δ is a parameter (potentially a vector of parameters) related to the discount function. $\widetilde{U}(W, d, S, \delta)$ is the present-discounted utility if incarcerated for S years, where d is the yearly cost of incarceration.[25]

Conditional on the robber's expectations about $Y(t)$ and $F(t)$, different observed durations could be driven by heterogeneity in U, W, δ, and d. It is convenient to simplify this rather general formulation of the robber's maximization problem. Since most robbers stay only a few minutes inside the bank, and since all of them have to face the first minute, we approximate the utility they get at the very beginning of their criminal act. We start by considering a first-order Taylor approximation around the time they enter the bank branch ($t = 0$).[26]

With the first-order approximation one can divide the maximization problem by the marginal utility of wealth at time 0, rearrange terms, and rewrite the maximization problem as:

$$\begin{gathered}\max_t [1 - F(t)]E[Y'(t)]t - F(t)D, \\ D = [U(W, \delta) - \widetilde{U}(W, d, S, \delta)]\frac{\partial W}{\partial U(W, \delta)}.\end{gathered} \tag{2}$$

recurrent offenders (Mastrobuoni, 2014).

[24] Robbers can also be arrested after exiting the bank (ex-post). To the extent that the amount of time spent in the bank influences the probability of ex-post arrest, then this should also enter the maximization problem. We also estimated an extended version of the model that took this into account, but the effect of time spent in the bank on ex-post arrest was extremely small and statistically insignificant from zero. As a result, we focus on the version of the model without this additional component.

[25] Here we are implicitly assuming that there is no uncertainty with respect to the sentence. For most of the analysis this assumption is not necessary and one could simply rewrite the utility while incarcerated $\widetilde{U}(W, d, \delta)$ as an expectation over the distribution of S.

[26] The approximation is $U(W + Y(t), \delta) \approx U(W, \delta) + \frac{\partial U(W,\delta)}{\partial W} Y'(t)\, t$, where $Y' = \frac{\partial Y}{\partial t}$, and at time 0 the haul is 0 (zero input, zero output), or $Y(0) = 0$.

The difference, $U(W,\delta) - \widetilde{U}(W,d,S,\delta)$, captures the utility change when incarceration begins. By multiplying this expression by $\frac{\partial W}{\partial U(W,\delta)}$, we transform this from utility into a monetary measure, D, which we will define as the disutility of prison. $D = D(U,W,d,\delta)$ measures the compensating variation, or the amount of money the robber would be willing to pay to avoid the expected prison time. In Appendix B we show that under a few additional assumptions, a similar relationship can be obtained using a second-order Taylor approximation to the utility function. In this case the willingness-to-pay to avoid prison accounts for risk preferences in utility.

The optimal duration of a bank robbery t^* is determined by equating the costs and benefits of staying an additional minute[27]

$$-F'(t^*)[E[Y'(t^*)]t^* + D] + [1 - F(t^*)]E[Y'(t^*) + Y''(t^*)t^*] = 0. \tag{3}$$

As we discuss in Section 3, we will model the total haul $Y(t)$ as proportional to t, which simplifies this expression as $Y'(t) = y$ and $Y''(t) = 0$.

We can then solve the first-order condition for the unobserved disutility of prison D. The individual-specific compensating variation for each successful robber i is given by:

$$D_i = \frac{1}{\lambda_i(t_i^*)}E[y_i] - E[y_i]t_i^*, \tag{4}$$

where $\lambda(t^*) \equiv \frac{F'(t^*)}{1-F(t^*)}$ is the hazard rate of arrest.[28] What this implies is that if we can estimate the expected haul and the hazard rate, then we can use these estimates, combined with the observed robbery duration, to compute the unobserved, individual-specific disutility of prison.

All the arguments of the disutility of prison D introduce potential heterogeneity in the observed behaviour of robbers. Robbers may appear to be more reckless (lower D) either because the marginal utility of wealth is very high (liquidity constrained, low W), they have a low valuation of prison time (low d), they use a *modus operandi* that minimizes prison time S, or, finally, because they do not care about the future (low δ). While the relationship in equation (4) identifies the disutility of prison D, the underlying sources of heterogeneity in preferences are not identified.

[27] Here and throughout the paper we assume that, conditional on entering the bank, robbers choose an interior solution, and that the objective function is differentiable.

[28] The optimal robbery duration t^* is only observed for those individuals that successfully leave the bank before the police arrive. For the approximately 4% of robberies for which this is not the case, we observe only a lower bound for t^*, which one can show equates to an upper bound on D.

3 Empirical Model

The next step is to devise an empirical strategy to estimate the expected haul and hazard functions. At least since RAND's 1980 study, "Doing Crime: A Survey of California Prison Inmates," criminals have been shown to have expectations about the costs and benefits of their actions. Robbers will have expectations about the rate of accumulation of money and the inherent risk of being caught while inside the bank. These two expectations are likely to depend on characteristics of the robbery strategy (e.g., using a weapon or wearing a mask), and characteristics of the target (e.g., presence of a guard, number of security devices), which will be influenced by the perpetrator's past experiences.

As mentioned in the introduction, we will use objective measures of individual expectations. Prior to entering the bank, robbers will have expectations about the haul and the likelihood of arrest, based on the chosen modus operandi, characteristics of the target, as well as their ability. In order to measure these expectations we will estimate the relationship between the haul and hazard of arrest as functions of characteristics of the robbery. Since ability is unobserved to the researcher, this presents a challenge for estimation. For example, an individual with a high ability might expect both a larger haul and, at the same time, a lower hazard of police arrival. This generates a correlation between these two objects, which left unaccounted for would bias our estimates of disutility. In order to deal with unobserved heterogeneity in ability, we estimate the expected haul and hazard of arrest jointly, using a factor model to control for unobserved ability and the correlation it generates in the outcomes (see e.g., Anderson and Rubin, 1956, Jöreskog and Goldberger, 1975, and Heckman *et al.*, 2006). In what follows we lay out the empirical model, describing each of the components and our estimation strategy.

3.1 *Components*

3.1.1 *Haul*

We model the haul as proportional to the time spent in the bank: $Y = y * t$, where y denotes the marginal haul (haul per minute).[29] Without observing individual minute-by-minute money gathering, we cannot directly verify this proportionality assumption. However, as some supportive evidence, in Figure 1 we plot the raw data on hauls as a function of time spent in the bank. We also include parametric and non-parametric regression lines. Circles are proportional to the number of robberies with particular haul

[29] For robberies involving multiple robbers we first divide the total haul by the number of robbers to construct Y.

and duration combinations. The solid line shows a locally polynomial regression of degree 3 with asymptotically optimal constant bandwidth (Fan and Gijbels, 1996). The dashed line corresponds to a linear regression fit. The non-parametric fit is similar to the linear fit, suggesting that at least the cross-sectional relationship between the total haul and the duration of the robbery is approximately linear.[30]

Furthermore, a linear technology seems consistent with the typical actions taken by the offenders: i) enter the bank and walk to the teller, which usually takes only a few seconds unless the offender has to stand in line; ii) ask the teller for the money, typically the teller's direct cash holdings, which also takes a few seconds; iii) collect and store the cash, iv) eventually move to the next teller to collect additional cash. Of these actions the last two are probably the most time consuming, and there is no apparent reason why robbers should expect convex or concave returns with respect to time, as long as there is enough cash available.[31] We therefore model the (log) haul per minute as a function of the characteristics of the robbery (x_i), unobserved ability (a_i), and a residual (ε_i^y):

$$\ln y_i = x_i'\alpha + \pi_y a_i + \varepsilon_i^y.$$

As noted above, many, if not all, of the characteristics of a robbery x_i are choices made by the robbers. As a result, they are potentially correlated with the unobserved ability of the robber, which makes the characteristics endogenous. In order to deal with this, we decompose ability into two components: a component that is correlated with x_i and an orthogonal residual $\tilde{a}_i \equiv a_i - E[a_i \mid x_i]$.[32] In essence, $\tilde{a}_i$ captures the part of ability that is not reflected in the choice of robbery characteristics. We can then rewrite the haul function as

$$\ln y_i = x_i'\tilde{\alpha} + \pi_y \tilde{a}_i + \varepsilon_i^y, \tag{5}$$

where $\tilde{\alpha}$ captures the direct effect of robbery characteristics on the haul, as well as indirect effects via unobserved ability.[33] This will be important to consider when interpreting the coefficients later on. The coefficient on residual ability π_y, however, is unchanged.

The expected haul (from the robber's perspective) is based on both observable robbery characteristics, as well as residual ability $\tilde{a}$. It is possible, however, that expectations

[30] Both a quadratic and a cubic relationship between haul and duration are rejected in favour of the linear one (p-value 0.26 and 0.21, regression results are available upon request).

[31] Since 95% of total hauls are below €55,700, it is also very unlikely that tellers run out of cash.

[32] See Mundlak (1978) and Chamberlain (1984) for related discussions in the context of fixed effects panel data models.

[33] We have assumed for simplicity that the expectation of a_i conditional on x_i is linear (i.e., $E[a_i \mid x_i] = \rho x_i$), although this assumption can be relaxed.

about the haul are updated while the robber is inside the bank, and thus in terms of equation (5), part (or all) of ε_i^y is known to the robbers when they make their decision of when to leave the bank. We revisit this in Section 4.5, in which we estimate an alternative specification of the model that takes this into account.

3.1.2 *Hazard of police arrival*

Letting T_p denote the random time of police arrival, with *pdf* f and *cdf* F, the hazard function for police arrival at time t_p is given by

$$\lambda\left(t_p\right) = \frac{f\left(t_p\right)}{1 - F\left(t_p\right)}.$$

We model police arrival as following an exponential distribution,[34] and model the constant hazard as a function of characteristics and ability as

$$\ln \lambda\left(t_{p_i} \,|\, x_i, \tilde{a}_i\right) = x_i' \tilde{\beta} + \pi_p \tilde{a}_i, \tag{6}$$

where, as in the model for the haul, we have written the hazard as a function of residual ability $\tilde{a}_i$.

3.1.3 *Time spent in the bank / disutility of prison*

Recall from equation (4) that we need expectations about the haul and hazard of arrest in order to compute the disutility of prison. In order to estimate the hazard, we need to know the arrival time of police for all observations. In the data, however, the observed duration of the robbery is the minimum of the time of police arrival t_p and the (ex-ante) chosen optimal duration of the robbery t^*. Therefore, we only observe the arrival time of police for those robbers who had not already left the bank before police arrived. Since leaving the bank is a decision of the robbers, we also need to take this selection into account by modelling t^*, which implies that we need a model for the disutility D.

Let T^* be a random variable denoting the time at which the robbers would have optimally chosen to leave the bank. The probability of police arrival at time t, conditional on not having already arrived, and conditional on the robbers having not yet left the bank is given by

[34] In a previous version of the paper, estimates were obtained from a reduced form hazard model using both an exponential and Cox proportional hazard model. The results were very similar between the two specifications, and almost indistinguishable where the majority of the mass of durations is distributed. Therefore, we decided to focus on the exponential model for simplicity.

$$\Pr\left(\text{Arrest at time } t \ \middle| \text{not arrested yet, still in bank}\right) = \lambda\left(t\right) \frac{1}{\Pr\left(T^{*} > t\right)}.$$

Essentially we have a competing risks model, in which no one is censored (every robbery either ends with police arrival or the robbers leaving the bank). In order to estimate the hazard of police arrival, we also need to estimate the distribution of optimal robbery duration T^{*} to compute the probability that the robbery is ongoing: $T^{*} > t$.

Recall that optimal time spent in the bank T^{*} is given by the solution to the first-order condition in equation (4). If we solve this equation for time we have

$$T^{*} = \frac{1}{\lambda\left(t\right)} - \frac{D}{E\left[y\right]}. \tag{7}$$

Note that while the disutility term D is known to the robbers, it is unknown to the econometrician. Therefore in order to obtain the distribution of T^{*}, we need the distribution of disutility. Similarly to the haul and hazard of police arrival, we allow the disutility of prison to depend on characteristics and ability:

$$\ln D = x_i'\tilde{\delta} + \pi_d \tilde{a}_i + \varepsilon_i^d. \tag{8}$$

In particular, ability is likely to affect the disutility of prison through higher ability individuals having a higher opportunity cost of incarceration. Putting this together with equation (7) gives us our equation for T^{*}:

$$T_i^{*} = \frac{1}{\lambda\left(t_i^{*} \,|\, x_i, \tilde{a}_i\right)} - \frac{e^{x_i'\tilde{\delta} + \pi_d \tilde{a}_i + \varepsilon_i^d}}{E\left[y_i \,|\, x_i, \tilde{a}_i\right]}. \tag{9}$$

This equation implies that, conditional on x_i and $\tilde{a}_i$, variation in T^{*} is driven by the residual in disutility ε_i^d.

3.1.4 *Zero hauls and arrest after exiting the bank*

Approximately 8% of the robberies in our data yield a haul of zero, and therefore the log haul is not defined. In order to incorporate the zero haul robberies, we include an extra equation that models the probability of a non-zero haul as a function of the same variables (x and $\tilde{a}$). Letting $O_i = 1$ indicate a strictly positive haul and $O_i = 0$ indicate a haul of zero

$$\Pr\left(O_i = 1 \,|\, x_i, \tilde{a}_i\right) = \Phi\left(x_i'\tilde{\psi} + \pi_o \tilde{a}_i\right), \tag{10}$$

where Φ denotes a standard normal *cdf*.

Finally, in addition to observing if and when robbers are arrested during the commission of the robbery, we also observe an indicator for whether the police make the arrest at some point after the robbery. While this information is not needed to estimate the model, the estimates from this equation are interesting on their own (in terms of understanding how robbery traits are related to ultimate arrest). Furthermore, since ex-post arrest is also potentially correlated with ability (higher ability robbers might leave fewer and less informative clues to lead to their capture), adding this to the model provides additional information to help pin down the unobserved ability of the robbers. Letting $C_i = 1$ denote an arrest after exiting the bank (conditional on exiting the bank), we have

$$\Pr\left(C_i = 1 \mid x_i, \tilde{a}_i\right) = \Phi\left(x_i'\tilde{\gamma} + \pi_c \tilde{a}_i\right). \tag{11}$$

3.2 *Estimation*

In the data we observe one of three mutually exclusive discrete arrest outcomes: 1) caught in the bank, 2) caught out of the bank, 3) not caught. For those caught in the bank, we observe a continuous measure of time at which the police arrive. For the other two, we observe a continuous measure of time spent in the bank. For all of these outcomes we observe a continuous measure of the haul.

Our model is based on equations (5), (6), (9), (10), and (11).[35] We assume that the residuals in the haul equation and disutility equation, ε^y and ε^d, are normally distributed with mean zero and standard deviations σ_y and σ_d that we will estimate. Residual ability $\tilde{a}_i$ is assumed to be normally distributed as well. Our factor model setup requires some normalizations, since unobserved ability has no units. We do this by normalizing the mean and variance of residual ability to be zero and one, respectively.[36] Together these distributional assumptions imply that the marginal haul is log-normally distributed, consistent with the empirical distribution.

We estimate the model by maximizing the likelihood, which allows us to take into account the dependence across equations via residual ability $\tilde{a}_i$. In essence, correlation in the unobserved components of the outcomes (haul, arrest, time spent in the bank), identify the importance of the factor (residual ability) in each outcome. See Appendix A for a complete characterization of the likelihood.

[35] In each of these equations, we include both province-level fixed effects and year-by-month fixed effects to control for unobserved location- and time-specific characteristics.

[36] Technically we also need to normalize the sign of the coefficient on ability in one of the outcome equations. We do this by normalizing the effect of ability to be positive in the haul equation.

4 Results

In Table 3, we report estimates from our model, which we label "Statistical Expectations" to reflect that our estimates of the robbers' expectations are based on the statistical model described above. Recall from Section 3 that our estimates of the coefficients on observables (such as the use of a firearm, or the presence of guard), combine the direct effect of the variable, as well as the indirect effect via the correlation with unobserved ability. We are, however, able to estimate the causal effect of unobserved ability on the various outcomes via the coefficient on residual ability, $\tilde{a}$.

4.1 *Haul*

Columns 1 and 2 of Table 3 present estimates of the coefficients from the model for the haul in equations (10) and (5), respectively. In column 1, we have estimates of the probability of obtaining a positive haul, which occurs in 92% of the robberies, and in column 2 we have estimates of the marginal haul equation.

Robbers who use weapons (either firearms or knives/other) are more likely to have a positive haul (7 percentage points) and have higher marginal hauls (25% and 14% higher). Working in groups is also associated with a higher probability of having a positive haul (4-5 percentage points). The marginal haul is lower per person, which is not surprising given that they have to split the haul, but the decrease is less than proportional to the number of robbers, implying a larger overall haul. This decreasing returns to scale in the number of robbers could be due to specialization among the robbers. For example, some robbers could be more focused on securing the escape, as opposed to participating in money gathering. Wearing a mask is associated with a 15% increase in marginal haul, perhaps because the mask induces fear in the victims, or as a signal of higher ability robbers.

Robbers who target banks with smaller cash holdings are less likely to receive a positive haul, as would be expected. Banks with more employees lead to larger marginal hauls, perhaps because there are more workers to collect the cash for the robbers. The least profitable robberies are those that happen in the early afternoon, while the most profitable ones are those that happen around opening and closing time.[37] Having more security devices, security devices with more features, a larger number of invisible security features, and a security guard are all associated with lower marginal hauls, and to some extent lower

[37] The probability of a positive haul is lower, but this is offset by a larger marginal haul (although the latter effect is not statistically significant).

likelihoods of a positive haul.

Not surprisingly, higher ability generates both a larger probability of a positive haul as well as larger marginal hauls. Since unobserved ability does not have any units, we will use the effect of ability on the marginal haul as a benchmark.[38] A 1 unit increase in ability is found to have a 102% increase in marginal haul. Therefore, a 0.98 unit increase in ability ($\frac{100}{102}$) is associated with an 100% increase in marginal haul, and a 0.5 percentage point increase in the probability of a positive haul.

4.2 *Hazard of Police Arrival*

Column 3 of Table 3 shows estimates of the hazard function for police arrival in equation (6). Working in groups is associated with a reduction in the hazard of about 40%, consistent with the specialization story discussed above, in which some of the robbers work to decrease the probability of apprehension at the expense of a larger per-person haul. This effect could also be explained by higher ability robbers choosing to work together in groups, and this higher ability also translating into a smaller hazard. Robbers who wear masks have lower hazards of 40%, perhaps, as with the haul, because it scares victims or signals higher ability.

Escaping by foot or car is associated with much larger hazards of police arrival. The excluded category here is that the means of transportation is not observed, so one likely explanation for these results is that robbers who manage to conceal their method of transport are more difficult to detect and/or are higher ability criminals.

The number of employees and size of the bank are also important, as more employees and larger banks are associated with higher hazards, perhaps because there are more people available to alert the police. Similarly, the presence of a guard is strongly associated with police arrival (increased hazard of about 50%). The coefficient on late afternoon robberies is negative and quite large in magnitude. Since this represents closing time for most banks in Italy, this suggests that banks are more vulnerable at this time, perhaps because bank employees (tellers and guards) are either less able or less willing to aid police near closing time. This may have a compounding effect by attracting higher ability robbers as well.

Finally, the effect of ability on police arrival is strongly negative, consistent with the idea that more capable robbers take actions that are less likely to alert the authorities. Using the effect of ability on the marginal haul as a benchmark, a difference in ability that corresponds to a doubling of the haul leads to a decrease in the hazard of police

[38] This is sometimes referred to as anchoring (see Cunha *et al.*, 2010).

arrival of about 14%.

4.3 *Arrest After Exiting the Bank*

In column 4, we report estimates from equation (11) related to the probability of subsequent arrest, for those robbers that left the bank before the police arrived.[39] Most of the variables that significantly predict the hazard of police arrival have similarly estimated effects on subsequent arrest, which is intuitive.

Working as a group leads to a large, roughly 2 percentage point, decrease in the probability of subsequent arrest. Having the method of transport be unobserved and wearing a mask also decrease this probability significantly (about 2 percentage points for each). This makes sense, as these are likely aid significantly in avoiding detection by police.

Somewhat surprisingly, having more security devices is associated with a decrease in the probability of subsequent arrest, although the effect is not particularly large. One additional device lowers the probability by 0.4 percentage points. Examining the effect of security devices overall, their main role seems to be that of reducing the haul, and not of increasing the chances of apprehension.

Having more employees increases the likelihood of arrest, again perhaps due to having more witnesses. The commission of a robbery in the late afternoon perfectly predicts subsequent arrest: no late afternoon robbers who successfully exited the bank before police arrival were later apprehended. As discussed in the results for the hazard of police arrival, this is consistent with bank employees being focused on closing the bank for the day or more cooperative knowing that they are about to leave, and also with higher ability robbers targeting this time as a result of these benefits.

Finally, higher ability robbers are also more likely to avoid ex-post arrest. An increase in ability leading to a doubling of the marginal haul decreases the probability of subsequent arrest by 0.8 percentage points, a drop of around 25%.

4.4 *Time Spent in the Bank / Disutility of Prison*

Finally, in column 5 we present estimates of the relationship between robbery characteristics and the disutility of prison from equation (8). Recall that while disutility is

[39] As discussed earlier, we also estimated a version of the model in which we allowed this probability of subsequent arrest to depend on the time spent in the bank, under the idea that perhaps robbers who spent more time left more clues for police. The coefficient on time was very small both economically and statistically, and including time had almost no effect on the other estimates.

unobserved, it is related to the observed optimal robbery duration via equation (9). A positive coefficient indicates a larger disutility of prison (i.e., going to prison is more costly). We find that higher ability robbers have a higher disutility of prison. High ability leads to larger hauls and lower probabilities of arrest. These both reflect higher opportunity costs of spending time in prison, and therefore higher disutilities. A difference in ability associated with increasing the marginal haul by 100% corresponds to a similar increase in disutility of 115%.

Robbers with different disutilities target different banks and use different *modus operandi*. Therefore, a positive (negative) correlation between robbery characteristics and disutility (as displayed in column 5) is suggestive of these robbery traits being selected by higher (lower) ability robbers.

There are also direct links between some characteristics and the disutility of prison. In Italy, there are sanctioning rules requiring that judges adjust sentences proportionally to the aggravation of the robbery. Specifically, Art. 628 of the penal code sanctions masked robberies, robberies perpetrated by more than one criminal, and robberies where firearms are used more strongly than “simple" robberies (*rapina semplice*). This is reflected in the estimated coefficients for masks and firearms, as disutility is found to be 55% and 50% higher, respectively, although the coefficient for firearms is not precisely estimated. Using detailed data from sentencing outcomes for bank robberies in Turin, Italy, in the Online Appendix O2, we find that sentences are at most about 7% and 39% higher for robberies involving masks and firearms, respectively, suggesting that only part of this higher disutility is coming from longer sentences. The data from Turin also suggest that working in groups is associated with slightly longer sentences, although we find no relationship between disutility and working in pairs and a negative one for groups of three or more. This suggests that working in groups of three or more is not ideal, as the reduction in risk is too small to offset the smaller per-capita haul.[40]

Not surprisingly, travelling to the robbery by foot and targeting a bank with a security guard are both consistent with lower ability offenders. There is also evidence that higher ability robbers target banks in the late afternoon around closing time.

[40] This does not imply that sentencing enhancements based on working in groups are not warranted. Robberies involving groups of three or more offenders are more harmful, as they are associated with both larger total hauls and lower probabilities of apprehension.

4.5 *Statistical Expectations and Perfect Foresight*

Prior to entering the bank, robbers will have expectations about the haul and the likelihood of arrest, upon which they base their decisions regarding the optimal time to exit the bank. It is difficult to know whether such expectations are updated during the short time robbers spend inside the bank. They may get updated as the robbers gather information inside the bank. For example, the robber might learn that tellers are cooperative, thereby accelerating the accumulation of money. Alternatively they might learn that cash reserves are particularly low that day, lowering the expected return.

In line with the literature on expectations we label the two extreme scenarios:

1. statistical expectations, so that robbers who are alike in terms of *modus operandi*, target, and ability, are assumed to have the same prior expectations that do not update while inside the bank branch during the robbery.[41]

2. perfect foresight, so that the individual expectations are simply the individual realizations[42]

In the first case, no additional information is obtained, and the expectation used to make the decision of how long to stay in the bank is unchanged from the initial expectation. This is our baseline specification as described above. In the second case, the expectations of robbers are updated very quickly. Therefore the expected haul, upon which they base their decisions, will correspond to the realized one. The truth is likely to lie somewhere in between, and thus these two cases form bounds on the true underlying expectations that robbers have about the haul.

Since the perfect foresight expectation of the haul is the observed haul, it captures the realized uncertainty about the haul. Expected hauls are therefore more dispersed under perfect foresight. In turn this leads to an increase in the dispersion of the disutilities implied by the model. In order to see why this is the case, consider a robber that obtains a larger than anticipated haul. If the robber perfectly internalizes this when deciding how long to stay in the bank (perfect foresight), this will lead him to want to stay in the bank longer (see equation (4)). In order for the observed robbery duration to be consistent with this, it then must be the case that the disutility of prison is larger as well, relative to the case in which this information is not internalized (statistical expectations). As a

[41] As an early example of statistical expectations of criminals, Witte (1980) uses post-release experiences of individuals specializing in a similar crime type to estimate expectations on the potential risks.

[42] Most aggregate crime regressions assume that criminals have perfect foresight. See Wolpin (1978) for an early treatise on perfect foresight of criminals.

result, larger dispersion in expected hauls will translate to larger dispersion in disutilities. These two frameworks thus also provide bounds on the true underlying disutilities.

Unlike for the haul, there are few signals available to the robbers that could change risk perceptions over the duration of the robbery. The most important signal is likely to be the arrival of a police patrol, but by then it is also usually too late to matter. Moreover, realized risk of apprehension does not change continuously (one is either apprehended or not), meaning that one cannot use realizations to approximate perceptions. As a result, we focus on the statistical expectations framework for modelling the hazard of arrest.

Since we have no direct data to inform us as to how much information robbers collect during the commission of a robbery and therefore how quickly they update their expectations regarding the haul, we also estimate a version of the model under the bounding case of perfect foresight expectations about the haul. In the context of our model described above, this entails replacing the expected haul per minute in equation (4) with the realized one, and similarly in equation (9).

The estimates from this perfect foresight specification are provided in Table 4. Since the model equations are all estimated jointly, all of the model parameter estimates are subject to change. However, as the results in Table 4 illustrate, the parameter estimates are overall quite similar between the two models. The main difference is in the estimated dispersion in disutilities, captured by the standard deviation of the residual in the disutility ε_i^d, which is larger for the perfect foresight model, as expected. The estimated effects of ability in the various equations are also somewhat greater, although the increase is not particularly large. Overall the main effect of accounting for the possibility that robbers accumulate additional information about the haul during the robbery is a more dispersed distribution of disutilities.

5 Estimating the Individual-Specific Disutility of Prison

Our estimates discussed in the previous section provide us with estimates of the dispersion in disutility and of the relationship between disutility and robbery characteristics, but not the actual disutilities themselves. In order to estimate the disutilities, we use equation (4), plugging in our estimates of the expected haul and the hazard of police arrival, to identify the unobserved disutilities of prison for each observation.[43] Both of these objects depend on the (residual) ability of the robbers, $\tilde{a}_i$, which is unobserved to the econometrician.

[43]Note that our estimates of the distribution of disutility of prison correspond to the population of robbers that decided to attempt to rob a bank, and do not necessarily reflect the distribution for the population at large.

However, our model estimates can be used to compute an expected (residual) ability level for each observation, which can then be plugged into the expectations formulas.[44]

We begin by showing results comparing our estimates of the expected marginal haul (from the perspective of the robbers) for our bounding cases of statistical expectations and perfect foresight. For the statistical expectations model, this involves calculating the expected haul conditional on observed robbery characteristics and ability. Under the perfect foresight model, the expected haul equals the realized haul. We illustrate the estimates graphically in Figure 2 by plotting a line connecting the origin and the total expected haul, where the slope of each ray represents an expected marginal haul. The figure highlights that the variation in slopes for the perfect foresight model is noticeably larger compared to the statistical expectations model. This is expected, as the perfect foresight model incorporates uncertainty that the statistical expectations model does not.

Next we compute the hazard of police arrival. We use this, combined with the expected haul, to compute the disutility for each observation using equation (4). Recall that the equation for disutility depends on the optimal time spent in the bank t^*. For a fraction (about 4%) of our observations, the police arrive before the robbers leave the bank, implying that we observe a lower bound on t^*. As a result, the estimated disutilities for these observations represent an upper bound on disutility.

The *total* disutility of prison depends on the number of years robbers expect to spend in prison if arrested, and the rate at which they discount these future punishments. In Italy there are no official national statistics on prison time served by convicted bank robbers that condition on the *modus operandi*. Therefore, in order to translate our disutility estimates into a "yearly" disutility of prison (denoted d), we hand-collected detailed data on sentences for all bank robbers sentenced in the Piedmont region of Italy during the period of 2005-2007. These data cover 96 robbers, who participated in 324 bank robberies between 1993 and 2007. Unfortunately these data do not include information about the targeted branches, and therefore we cannot link them to the robberies in our main data. However, we can use these data to determine (to some extent) how sentence length varies with the characteristics of the robbery.[45] The average sentence length is 3.5 years,[46] and increases by 30% to 40% when robbers use firearms, by 10% to 20% when they operate in a group, and by 3% to 7% when they use a mask.

[44]This involves applying Bayes' Rule to recover the distribution of (residual) ability conditional on the data, and then integrating over that distribution to compute the expected value of ability.

[45]See Online Appendix O2 for details of this auxiliary data and how we calculated the expected sentence length conditional on robbery characteristics.

[46]This number is not far from the average sentence length of robbers convicted in Milan (Mastrobuoni, 2014).

There is very little empirical evidence in the literature on the extent to which criminal offenders discount the future. In general, if robbers discount future disutility with an annual discount factor of δ, then the relationship between the total disutility D and the yearly value d is given by $D = \sum_{t=0}^{S-1} \delta^t d = d\frac{1-\delta^S}{1-\delta}$, where S is the expected sentence length. The only paper we are aware of that provides a direct empirical estimate of criminal discounting is Mastrobuoni and Rivers (2016), which finds an average annual discount factor of 0.74 among criminal offenders in Italy.

5.1 *The Total and the Yearly Disutility of Prison*

Figure 3 shows the distribution of total disutility of prison (capped at €2,000,000) under each model. There is a mass of observations with zero disutility under the perfect foresight model corresponding to observations with zero hauls. For the statistical expectations model, the expected haul is always strictly positive, and thus so are the disutilities. In both cases, the estimated distribution of compensating variation (or disutility of prison time) is positively skewed and resembles a "log-normal" earnings distribution.

We also compute the implied yearly measures d using an annual discount factor of 0.7 to correspond to the estimates in Mastrobuoni and Rivers (2016), as well as with a discount factor of 1 for ease of interpretation.[47] These values are plotted in Figure 4.

Table 5 shows the percentiles of these distributions. The median yearly value is between €67,000 and €130,000, depending on which model and discount factor are used. This is consistent with what robbers can potentially earn in a year robbing banks.[48]

In line with the evidence shown in Figure 2, and consistent with what one would expect, the estimated disutilities that are based on the perfect foresight assumption lead to more dispersion in total disutilities compared to those found under statistical expectations. Moreover, the mass of robbers with zero realized hauls generates a mass of zero disutilities for the perfect foresight model. Despite these differences, the correlation between the two disutilities is 93%, and the two models imply similar information about the perceived cost of imprisonment.

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[47] See also Nagin and Pogarsky (2004); Jolliffe and Farrington (2009); Åkerlund *et al.* (2016); Mancino *et al.* (2016) for studies relating criminal behaviour to measures of future time preference elicited from survey questions.

[48] The median haul per robber is €5,300. Data collected from the Milan police (Mastrobuoni, 2017), in which serial bank robbers are tracked over time, show that the median number of days between bank robberies is 10. Given that the overall arrest rate is 6.6%, the expected number of robberies in a year is approximately 14. For a robber with the median frequency of robberies and the median haul, the anticipated yearly haul is close to €75,000, which is in line with the annual value of compensating variation that we find.

5.2 *Deterrence*

Given our estimates of disutility, we can ask the question, by how much would policy makers need to increase the disutility of prison in order to push the optimal robbery duration to zero. Using our estimates of the expected haul and hazard of police arrival, we calculate this for each observation by computing the value of the disutility D such that $t^* = 0$ in equation (4). Letting this value be denoted as $D_{t=0}$, and letting $D_{t=t^*}$ be the estimated value corresponding to the observed duration, we have that the percentage increase in disutility needed for robbers with an observed $t^* > 0$ to drive the duration to 0 is given by $\log D_{t=0} - \log D_{t=t^*}$. We then compute the associated percentage increase in sentence length needed to drive t^* to 0 for different values of the discount factor. (Note that for a discount factor of 1, the necessary percentage increase in disutility and sentence length are equivalent.)

Table 6 reports the percentage increase that drives different fractions of the robberies to zero durations. For example, for a discount factor of 0.7, for the statistical expectations model, the number in the first column shows that in order to drive 5% of the sample to a duration of zero one needs a 1% increase in sentence length. In order to do this for 25% of bank robberies, the penalties would have to increase by about 2%, etc.

Overall, and no matter how one models the expectations, criminal behaviour is predicted to be highly responsive to changes in the sanctioning system. Moreover, since sentence lengths for bank robbers are quite low in Italy, these percentage increases in sentence length would come at a relatively low cost to society. If we were to interpret a robbery duration of $t^* = 0$ to be "no robbery", then this implies substantial deterrent power from increasing sanctions. However, this calculation only takes into account the intensive margin decision of how long to stay in the bank, conditional on having entered the bank. If there is a fixed component of utility related to robbing banks, for example due to the rush of planning and executing a robbery, then further increases in sentence length would be necessary to deter these robberies.

Our main focus in this paper relates to the intensive margin decision of robbers of how long to stay in the bank. As a result, in the maximization problem described in equation (2) we only included components that varied with robbery duration t. If we let FR_i denote the fixed return to committing a robbery and account for arrests made after exiting the bank ($C_i = 1$), a more general maximization problem can be written as:

$$\max_{t_i} FR_i + \underbrace{[1 - F(t_i)]\,[1 - \Pr(C_i = 1)]}_{\text{Prob. of No Arrest}} E[y_i]t_i - \underbrace{[F(t_i) + (1 - F(t_i))\Pr(C_i = 1)]}_{\text{Prob. of Arrest}} D_i. \quad (12)$$

This equation generates the same solution for the optimal duration as the one to our original equation (2).

The total return to a robbery in equation (12) is then the sum of the fixed return FR_i and the remaining variable return which varies with duration. Given the observed robbery duration and our estimates of the expected haul and probability of arrest (both inside the bank and after exiting the bank), as well as the disutility associated with imprisonment, we can compute the expected variable return to a robbery (EVR_i).[49] Under the assumption that the total expected return should be greater than zero: $FR_i + EVR_i \geq 0$, we can compute a lower bound on FR_i for each observation that is equal to $-EVR_i$. These values are plotted in Figure 5. The average value is €12,782, which is about 150% of the average haul for a robbery (per robber). This suggests that even greater increases in sanctions are necessary to deter these individuals from committing robberies.

In an attempt to interpret this additional reward, we note that bank robbery (and more generally robbery) differs from most other crimes in that there is both a violent and financial gain component. While financially motivated crimes can be explained in part by the monetary rewards, less is known in the literature as to what drives individuals to commit violent offences. Our dataset on bank robberies thus provides us with a unique opportunity to quantify (in monetary terms) the value of the violent component of crime. One interpretation of the fixed component of crime described above, is that it captures the rush that offenders receive from committing a violent act. The fact that we can measure the monetary rewards to crime allows us to quantify this rush (in our case a lower bound), which is the approximately €12,000 discussed above.

5.3 *Heterogeneity*

The estimates in Tables 3 and 4 identify the robbery characteristics that are most strongly associated with differences in hauls and apprehension rates. For hauls, the use of a weapon and/or a mask leads to larger hauls, as does targeting banks with fewer security devices and no guards. Regarding arrests, working in groups, wearing a mask, and targeting banks with no security guard and few employees are associated with a decreased likelihood of getting caught.

Our estimates suggest that judges and lawmakers may want to target these robbery characteristics (in terms of sentence enhancements) in order to reduce the harm created

[49] Since the expectations here are from the perspective of the robber before entering the bank, we use the estimates corresponding to our baseline model of statistical expectations that do not incorporate information obtained during the robbery.

by bank robberies. There is evidence that this is already occurring in Italy and elsewhere, for example in US state and federal legislation, particularly for crimes involving firearms, groups of offenders, and masks. One caveat to this is that our estimates reflect both the causal effects of these characteristics as well as the indirect effects of the ability of those individuals who select them. Robbers (particularly high ability ones) may respond to an increase in the penalty for certain robber characteristics by simply selecting different ones, as opposed to not committing a robbery, partially mitigating the deterrent effect.

Ideally, one would like to target the high ability offenders directly, since these robbers cause the most damage (more money lost and more repeat offences). This is challenging though because ability is unobserved. One additional benefit of our estimates is that they suggest that a broader policy instrument could have a similarly targeted impact. We find that higher ability offenders, in addition to having improved outcomes, have a larger disutility of prison, possibly due to a higher opportunity cost of imprisonment. As a result, they are likely to be more sensitive to increases in sentence length. By increasing sentences overall, an important implication is that high ability offenders are indirectly and disproportionately targeted.[50]

6 Conclusions

Using unique and detailed data on almost 5,000 Italian bank robberies, we estimate how the haul and likelihood of arrest vary with characteristics of each robbery, including the unobserved ability of the robbers. Using information on the observed robbery duration we estimate individual-specific values of the compensating variation of imprisonment. We find evidence of large differences across offenders. Our estimates provide strong evidence that unobserved ability of robbers leads to systematically better outcomes for these offenders: larger hauls and lower arrest probabilities. We also find that higher ability offenders have a larger disutility of prison, potentially due to the opportunity cost of being incarcerated.

Policy makers and law enforcement have several instruments through which they can attempt to reduce crime. Our results indicate substantial heterogeneity in the disutility of prison (see Table 5 and Figures 3 and 4). This suggests that different policies are needed to effectively target individuals at different points in the distribution of disutility. Our finding that the disutility of prison is positively related to ability (which leads to larger

[50]Durlauf *et al.* (2010) describe a similar, but oppositely signed, effect in the context of the deterrent effect of the death penalty. They show that when there is heterogeneity in preferences for punishment (in their case the death penalty), then those individuals most likely to be deterred are the least likely to commit a crime in the first place, dampening the deterrent effect.

hauls and lower apprehension probabilities) implies that increased sentence lengths disproportionately target higher ability offenders.[51] However, for individuals with relatively low valuations of prison, increasing sentences or the probability of apprehension is likely to have much smaller effects on behaviour. For these individuals, policies which serve to increase the opportunity costs of crime could be more effective, and provide an alternative to increases in policing or sentencing.

Overall, our results highlight the benefit of collecting and analysing data at the individual level for crime research (Witte, 1980). By having data on individual offences, we are able to not only identify the presence of heterogeneity in the perceived cost of imprisonment, but we can measure the relationship with the underlying, unobserved ability of the offenders, and use this information to inform the design of criminal policy. In the future, researchers can use the method outlined in this paper to study other illegal acts that also involve intensive margin decisions.

Appendix A: Likelihood Function

Observations in our data can be placed into one of three mutually exclusive, discrete outcomes: 1) caught in the bank, 2) caught out of the bank, 3) not caught. For the outcome caught in the bank, we observe a continuous measure of time at which the police arrive. For the other two, we observe a continuous measure of time spent in the bank. For all of these outcomes we observe a continuous measure of the haul.

Letting θ denote the vector of parameters to be estimated, we can write the likelihood as the sum across the likelihood of the three discrete outcomes. The likelihood for the first outcome, conditional on the observed data, is denoted as $L(\theta; y, t_p, 1 \mid x)$, and is equal to the probability of observing a marginal haul equal to y, a time at which the police arrive of t_p, and the probability of the police arriving before the robbers leave the bank. With a slight abuse of notation, let g denote a generic density function. Let $\mathit{\Phi}_k$ and ϕ_k, for $k \in \{\ln \tilde{a}, \ln T^*, \ln y, O, C\}$, denote a *cdf* and *pdf* of a normal random variable, and let *Exp* and *exp* denote the *cdf* and *pdf* of the exponential distribution.[52] The likelihood for

[51] It is worth noting that in the US, where sanctions are significantly more severe, bank robberies are believed to be mostly the work of amateurs (Weisel, 2007; Department of Justice, 2003).

[52] We assume that the residual in the disutility equation is log-normally distributed, which implies that T^* is also log-normally distributed (conditional on $\tilde{a}$ and x).

case 1) is then given by the following

$$
\begin{aligned}
L\left(\theta;y,t_p,1\,|\,x\right) &= g\left(y,t_p,T^*>t_p\,|\,x;\theta\right)\\
&= \int g\left(y,t_p,T^*>t_p\,|\,x,\tilde{a};\theta\right)\phi_{\ln\tilde{a}}\left(\ln\tilde{a};\theta\right)d\tilde{a}\\
&= \int\left[1-\Phi_{\ln T^*}\left(\ln t_p\,|\,y,t_p,x,\tilde{a};\theta\right)\right]g\left(y,t_p\,|\,x,\tilde{a};\theta\right)\phi_{\ln\tilde{a}}\left(\ln\tilde{a};\theta\right)d\tilde{a}\\
&= \int\left[1-\Phi_{\ln T^*}\left(\ln t_p\,|\,y,t_p,x,\tilde{a};\theta\right)\right]g\left(y\,|\,x,\tilde{a};\theta\right)exp\left(t_p\,|\,x,\tilde{a};\theta\right)\phi_{\ln\tilde{a}}\left(\ln\tilde{a};\theta\right)d\tilde{a}\\
&= \int\left[1-\Phi_{\ln T^*}\left(\ln t_p\,|\,y,t_p,x,\tilde{a};\theta\right)\right]\\
&\quad\times\left[\Phi_o\left(x,\tilde{a};\theta\right)\phi_{\ln y}\left(\ln y\,|\,x,\tilde{a};\theta\right)\right]^O\left[1-\Phi_o\left(x,\tilde{a};\theta\right)\right]^{1-O}\\
&\quad\times exp\left(t_p\,|\,x,\tilde{a};\theta\right)\phi_{\ln\tilde{a}}\left(\ln\tilde{a};\theta\right)d\tilde{a}.
\end{aligned}
$$

The second equality follows from the definition of a conditional density function and allows us to to express the likelihood as the integral over the unobserved residual ability $\tilde{a}$. The third equality follows from the definition of a conditional density function and the fact that the haul per minute and the arrival time of police do not depend on the residual in the disutility of prison, which is the residual in T^*. The fourth equality follows from the fact that conditional on the observed data x and residual ability $\tilde{a}$, the haul per minute and police arrival time are independent. The fifth equality accounts for zero hauls, where recall that $O=1$ denotes a strictly positive haul, and $O=0$ otherwise.

For cases 2) and 3) robbers were not arrested inside the bank, and what distinguishes them from each other is whether or not an arrest was made outside of the bank, conditional on successfully leaving the bank. The corresponding likelihoods are given by:

$$
\begin{aligned}
L\left(\theta;y,t^*,2\,|\,x\right) &= g\left(y,t^*,T_p>t^*,C=1\,|\,x;\theta\right)\\
&= \int g\left(y,t^*,T_p>t^*,C=1\,|\,x,\tilde{a};\theta\right)\phi_{\ln\tilde{a}}\left(\ln\tilde{a};\theta\right)d\tilde{a}\\
&= \int\left[1-Exp_{T_p}\left(t^*\,|\,y,t^*,x,\tilde{a};\theta\right)\right]g\left(y,t^*,C=1\,|\,x,\tilde{a};\theta\right)\phi_{\ln\tilde{a}}\left(\ln\tilde{a};\theta\right)d\tilde{a}\\
&= \int\left[1-Exp_{T_p}\left(t^*\,|\,y,t^*,x,\tilde{a};\theta\right)\right]g\left(y\,|\,x,\tilde{a};\theta\right)\\
&\quad\times\phi_{\ln T^*}\left(\ln t^*\,|\,x,\tilde{a};\theta\right)\Phi_C\left(x,\tilde{a};\theta\right)\ln\phi_{\tilde{a}}\left(\tilde{a};\theta\right)d\tilde{a}\\
&= \int\left[1-Exp_{T_p}\left(t^*\,|\,y,t^*,x,\tilde{a};\theta\right)\right]\\
&\quad\times\left[\Phi_o\left(x,\tilde{a};\theta\right)\phi_{\ln y}\left(\ln y\,|\,x,\tilde{a};\theta\right)\right]^O\left[1-\Phi_o\left(x,\tilde{a};\theta\right)\right]^{1-O}\\
&\quad\times\phi_{\ln T^*}\left(\ln t^*\,|\,x,\tilde{a};\theta\right)\Phi_C\left(x,\tilde{a};\theta\right)\phi_{\ln\tilde{a}}\left(\ln\tilde{a};\theta\right)d\tilde{a}
\end{aligned}
$$

and

$$
\begin{aligned}
L(\theta; y, t^*, 3 \mid x) &= g(y, t^*, T_p > t^*, C = 0 \mid x; \theta) \\
&= \int g(y, t^*, T_p > t^*, C = 0 \mid x, \tilde{a}; \theta)\, \phi_{\ln \tilde{a}}(\ln \tilde{a}; \theta)\, d\tilde{a} \\
&= \int \left[1 - Exp_{T_p}(t^* \mid y, t^*, x, \tilde{a}; \theta)\right] g(y, t^*, C = 0 \mid x, \tilde{a}; \theta)\, \phi_{\ln \tilde{a}}(\ln \tilde{a}; \theta)\, d\tilde{a} \\
&= \int \left[1 - Exp_{T_p}(t^* \mid y, t^*, x, \tilde{a}; \theta)\right] g(y \mid x, \tilde{a}; \theta) \\
&\quad \times \phi_{\ln T^*}(\ln t^* \mid x, \tilde{a}; \theta)\left[1 - \Phi_C(x, \tilde{a}; \theta)\right] \phi_{\ln \tilde{a}}(\ln \tilde{a}; \theta)\, d\tilde{a} \\
&= \int \left[1 - Exp_{T_p}(t^* \mid y, t^*, x, \tilde{a}; \theta)\right] \\
&\quad \times \left[\Phi_o(x, \tilde{a}; \theta)\, \phi_{\ln y}(\ln y \mid x, \tilde{a}; \theta)\right]^O \left[1 - \Phi_o(x, \tilde{a}; \theta)\right]^{1-O} \\
&\quad \times \phi_{\ln T^*}(\ln t^* \mid x, \tilde{a}; \theta)\left[1 - \Phi_C(x, \tilde{a}; \theta)\right] \phi_{\ln \tilde{a}}(\ln \tilde{a}; \theta)\, d\tilde{a},
\end{aligned}
$$

where in both cases the fourth equality uses the fact that conditional on the observed data x and residual ability $\tilde{a}$, the haul per minute, police arrival time, and the probability of ex-post arrest are independent.

The model parameters consist of coefficients on observables x: $\left(\tilde{\alpha}, \tilde{\beta}, \tilde{\delta}, \tilde{\psi}, \tilde{\gamma}\right)$, coefficients on ability $(\pi_y, \pi_p, \pi_d, \pi_o, \pi_c)$, and the standard deviations of the residuals in the marginal haul and disutility equations (σ_y, σ_d). We integrate out the residual ability using Gauss-Hermite quadrature, and estimate the parameters via maximum likelihood.

Appendix B: Second-Order Approximation to Utility

In this appendix we show that under a few additional assumptions, we can derive a similar version of the utility maximization problem in equation (1) and associated willingness-to-pay to avoid prison in equation (4) in the main body, for a second-order approximation to the utility function.

There is a long history of second-order Taylor approximations of expected utility functions in economics and in finance. Among the best-known result of such approximations is the mean-variance decision in portfolio theory, which has been shown to fare quite well when compared to direct utility maximization (see, among others, Levy, 1974; Levy and Markowitz, 1979; Kroll *et al.*, 1984). Moreover, the approximation performs well even when using an empirical distribution of payoffs that are different from the Normal one (see Tsiang, 1972), or when the utility functions are not quadratic functions, for example, power functions (CRRA) or inverse exponential functions (see Tsiang, 1972; Hlawitschka, 1994).[53]

The second-order approximation to the expected utility (around $t = 0$) associated with staying in the bank for t minutes is

$$E[U(W + Y(t), \delta)] \approx U(W, \delta) + \frac{\partial U(W, \delta)}{\partial W} E[y]\, t + \frac{1}{2}\frac{\partial^2 U(W, \delta)}{\partial W^2} E\left[y^2\right] t^2,$$

where recall that we have modelled the total haul as $Y(t) = yt$. Under the assumption of power utility, a commonly used utility function with an implied constant relative risk aversion of r, the right-hand side can be rewritten as:

$$EU(W, \delta) + \frac{\partial U(W, \delta)}{\partial W} E[y]\, t + \frac{1}{2}\frac{\partial U(W, \delta)}{\partial W}\left(\frac{-r}{W}\right) E\left[y^2\right] t^2.$$

If we also assume that (unobserved) individual wealth is proportional to the expected total haul (with proportionality factor $\frac{k}{2}$),[54] divide this expression by the marginal utility of wealth, and replace for $E[U(W + Y(t), \delta)]$ in the utility maximization problem in equation (1), we obtain

$$\begin{aligned} \max_t V(t) &= [1 - F(t)]\left[U(W, \delta)\frac{\partial W}{\partial U(W, \delta)} + E[y]\, t - \frac{r}{k}\frac{E\left[y^2\right] t^2}{E(y)\, t}\right] \\ &\quad + F(t)\, \tilde{U}\left(W, \{c(j)\}_{j \leq S}, S, \delta\right)\frac{\partial W}{\partial U(W, \delta)}. \end{aligned}$$

Letting CV denote the coefficient of variation, where $CV = \frac{E\left(y^2\right) - E(y)^2}{E(y)^2}$, and recalling the definition of $D = \left[U(W, \delta) - \tilde{U}(W, d, S, \delta)\right]\frac{\partial W}{\partial U(W, \delta)}$, this can be rewritten as

$$\max_t V(t) = [1 - F(t)]\, E[y]\, t\left[1 - \frac{r}{k}\left(CV^2 + 1\right)\right] + F(t)\, D.$$

Finally, dividing through by $\left(1 - \frac{r}{k}\left(CV^2 + 1\right)\right)$, which does not depend on t, gives us

$$\max_t V(t) = [1 - F(t)]\, E[y]\, t + F(t)\, \breve{D},$$

[53] Moreover, Hlawitschka (1994) shows that second-order Taylor approximations work well even when Taylor expansions diverge.

[54] This assumption is not directly testable without data on the wealth holdings of bank robbers. However, since bank robbers tend to be recurrent offenders with large and predictable criminal hauls, we believe it is reasonable to assume that their wealth is proportional to the expected haul.

where $\breve{D} \equiv \frac{D}{\left(1-\frac{r}{k}(CV^2+1)\right)}$. This expression is equivalent to that in equation (1), except $\breve{D}$ replaces D. In both cases, the "D" term captures the willingness to pay to avoid prison. In this case $\breve{D}$, adjusts for risk preferences in the utility function via r. In other words, the more risk averse (loving) the individual, the more (less) they are willing to pay to avoid a given level of disutility associated with going to prison.

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References

Abrams, D.S. and Rohlfs, C. (2011). 'Optimal Bail and the Value of Freedom: Evidence from the Philadelphia Bail Experiment', *Economic Inquiry*, vol. 49(3), pp. 750–770.

Åkerlund, D., Golsteyn, B.H., Grönqvist, H. and Lindahl, L. (2016). 'Time Discounting and Criminal Behavior', *Proceedings of the National Academy of Sciences*, vol. 113(22), pp. 6160–6165.

Anderson, T.W. and Rubin, H. (1956). 'Statistical Inference in Factor Analysis', in (J. Neyman, ed.), *Proceedings of the Third Berkeley Symposium on Mathematical Statistics and Probability*, pp. 111–150, vol. 5, Berkeley: University of California Press.

Anwar, S. and Loughran, T.A. (2011). 'Testing a Bayesian Learning Theory of Deterrence Among Serious Juvenile Offenders', *Criminology*, vol. 49(3), pp. 667–698.

Ashenfelter, O. and Greenstone, M. (2004). 'Using Mandated Speed Limits to Measure the Value of a Statistical Life', *Journal of Political Economy*, vol. 112(1), pp. 226–267.

Becker, G.S. (1968). 'Crime and Punishment: An Economic Approach', *The Journal of Political Economy*, vol. 76(2), pp. 169–217.

Bernasco, W. (2010). *Offenders on Offending: Learning about Crime from Criminals*, Taylor & Francis.

Bhuller, M., Dahl, G.B., Løken, K.V. and Mogstad, M. (2016). 'Incarceration, Recidivism and Employment', NBER Working Paper No. 22648.

Chamberlain, G. (1984). 'Panel Data', in (K. J. Arrow and M. D. Intriligator, eds.), *Handbook of Econometrics.*, pp. 1247–1318, vol. 2, Elsevier.

Cook, P.J. (1983). *Robbery in the United States: An Analysis of Recent Trends and Patterns*, Washington, D.C.: National Institute of Justice.

Cook, P.J. (1985). 'Is Robbery Becoming More Violent? An Analysis of Robbery Murder Trends Since 1968', *The Journal of Criminal Law and Criminology*, vol. 76(2), pp. 480–489.

Cook, P.J. (1986). 'The Relationship between Victim Resistance and Injury in Noncommercial Robbery', *The Journal of Legal Studies*, vol. 15(2), pp. 405–416.

Cook, P.J. (1987). 'Robbery Violence', *The Journal of Criminal Law and Criminology*, vol. 78(2), pp. 357–376.

Cook, P.J. (2009). 'Robbery', in (M. Tonry, ed.), *The Oxford Handbook of Crime and Public Policy*, pp. 102–114, Oxford University Press.

Cunha, F., Heckman, J.J. and Schennach, S.M. (2010). 'Estimating the Technology of Cognitive and Noncognitive Skill Formation', *Econometrica*, vol. 78(3), pp. 883–931.

F. B. o. I. Department of Justice, ed. (2003). *Crime in the United States, 2002*, chap. Special Reports: Bank Robbery in the United States, Department of Justice, Federal Bureau of Investigation, pp. 301–312.

Drago, F., Galbiati, R. and Vertova, P. (2009). 'The Deterrent Effects of Prison: Evidence from a Natural Experiment', *Journal of Political Economy*, vol. 117(2), pp. 257–280.

Durlauf, S.N. and Nagin, D.S. (2011). 'The Deterrent Effect of Imprisonment', in (P. J. Cook, J. Ludwig and J. McCrary, eds.), *Controlling Crime: Strategies and Tradeoffs*, pp. 43–94, University of Chicago Press.

Durlauf, S.N., Navarro, S. and Rivers, D.A. (2010). 'Understanding Aggregate Crime Regressions', *Journal of Econometrics*, vol. 158(2), pp. 306–317.

European Commission (2007). 'Report on the Retail Banking Sector Inquiry', European Commission Directorate-General for Competition.

Fan, J. and Gijbels, I. (1996). *Local Polynomial Modelling and its Applications*, Chapman & Hall/CRC.

Federal Bureau of Investigation (2007). 'Headline Archives. Bank Robberies', FBI.

Harbaugh, W.T., Mocan, N. and Visser, M.S. (2013). 'Theft and Deterrence', *Journal of Labor Research*, vol. 34(4), pp. 389–407.

Harding, R.W. (1990). 'Rational-Choice Gun Use in Armed Robbery: The Likely Deterrent Effect on Gun Use of Mandatory Additional Imprisonment', *Criminal Law Forum*, vol. 1(3), pp. 427–450.

Heckman, J.J., Stixrud, J. and Urzua, S. (2006). 'The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior', *Journal of Labor Economics*, vol. 24(3), pp. 411–482.

Helland, E. and Tabarrok, A. (2007). 'Does Three Strikes Deter?: A Nonparametric Estimation', *Journal of Human Resources*, vol. 42(2), pp. 157–188.

Hjalmarsson, R. (2009). 'Crime and Expected Punishment: Changes in Perceptions at the Age of Criminal Majority', *American Law and Economics Review*, vol. 11(1), pp. 209–248.

Hlawitschka, W. (1994). 'The Empirical Nature of Taylor-Series Approximations to Expected Utility', *The American Economic Review*, vol. 84(3), pp. 713–719.

Jolliffe, D. and Farrington, D.P. (2009). 'A Systematic Review of the Relationship Between Childhood Impulsiveness and Later Violence', *Personality, Personality Disorder, and Violence*, pp. 41–61.

Jöreskog, K.G. and Goldberger, A.S. (1975). 'Estimation of a Model with Multiple Indicators and Multiple Causes of a Single Latent Variable', *Journal of the American Statistical Association*, vol. 70(351), pp. 631–639.

Kessler, D.P. and Levitt, S.D. (1999). 'Using Sentence Enhancements to Distinguish between Deterrence and Incapacitation', *Journal of Law & Economics*, vol. 42(1), pp. 343–363.

Kroll, Y., Levy, H. and Markowitz, H.M. (1984). 'Mean-Variance versus Direct Utility Maximization', *The Journal of Finance*, vol. 39(1), pp. 47–61.

Lee, D.S. and McCrary, J. (2017). 'The Deterrence Effect of Prison: Dynamic Theory and Evidence', in (M. D. Cattaneo and J. C. Escanciano, eds.), *Regression Discontinuity Designs: Theory and Applications*, pp. 73–146, Emerald Publishing Limited.

Levy, H. (1974). 'The Rationale of the Mean-Standard Deviation Analysis: Comment', *The American Economic Review*, vol. 64(3), pp. 434–441.

Levy, H. and Markowitz, H.M. (1979). 'Approximating Expected Utility by a Function of Mean and Variance', *The American Economic Review*, vol. 69(3), pp. 308–317.

Lochner, L. (2007). 'Individual Perceptions of the Criminal Justice System', *The American Economic Review*, vol. 97(1), pp. 444–460.

Lochner, L. and Moretti, E. (2004). 'The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-reports', *American Economic Review*, vol. 94(1), pp. 155–189.

Lochner, L.J. (2004). 'Education, Work, and Crime: A Human Capital Approach', *International Economic Review*, vol. 45(3), pp. 811–843.

Mancino, M.A., Navarro, S. and Rivers, D.A. (2016). 'Separating State Dependence, Experience, and Heterogeneity in a Model of Youth Crime and Education', *Economics of Education Review*, vol. 54, pp. 274–305.

Mastrobuoni, G. (2014). 'Police and Clearance Rates: Evidence from Recurrent Redeployments within a City', Mimeo.

Mastrobuoni, G. (2017). 'Crime is Terribly Revealing: Information Technology and Police Productivity', Mimeo.

Mastrobuoni, G. and Rivers, D.A. (2016). 'Criminal Discount Factors and Deterrence', Working Paper.

Miller-Burke, J., Attridge, M. and Fass, P.M. (1999). 'Impact of Traumatic Events and Organizational Response: A Study of Bank Robberies', *Journal of Occupational & Environmental Medicine*, vol. 41(2), pp. 73–83.

Mookherjee, D. and Png, I.P. (1994). 'Marginal Deterrence in Enforcement of Law', *Journal of Political Economy*, vol. 102(5), pp. 1039–1066.

Mundlak, Y. (1978). 'On the Pooling of Time Series and Cross Section Data', *Econometrica*, vol. 46(1), pp. 69–85.

Nagin, D.S. and Pogarsky, G. (2004). 'Time and Punishment: Delayed Consequences and Criminal Behavior', *Journal of Quantitative Criminology*, vol. 20(4), pp. 295–317.

OSSIF (2006). 'Rapporto sulle Spese del Settore Bancario per la Sicurezza Anticrimine nel 2006', OSSIF, Associazione Bancaria Italiana.

Polich, S., Peterson, M.A. and Braiker, H.B. (1980). *Doing Crime: A Survey of California Prison Inmates*, Santa Monica, CA: Rand Corporation.

Polinsky, A.M. and Shavell, S. (1992). 'Enforcement Costs and the Optimal Magnitude and Probability of Fines', *Journal of Law and Economics*, vol. 35(1), pp. 133–148.

Polinsky, A.M. and Shavell, S. (1999). 'On The Disutility and Discounting of Imprisonment and The Theory Of Deterrence', *Journal of Legal Studies*, vol. 28(1), pp. 1–16.

Raphael, S. (2006). 'The Deterrent Effects of California's Proposition 8: Weighing the Evidence', *Criminology & Public Policy*, vol. 5(3), pp. 471–478.

Reilly, B., Rickman, N. and Witt, R. (2012). 'Robbing Banks: Crime Does Pay - But Not Very Much', *Significance*, vol. 9(3), pp. 17–21.

Thaler, R. and Rosen, S. (1976). 'The Value of Saving a Life: Evidence from the Labor Market', in (N. E. Terleckyj, ed.), *Household Production and Consumption*, pp. 265–302, NBER Chapters, National Bureau of Economic Research.

Tsiang, S.C. (1972). 'The Rationale of the Mean-Standard Deviation Analysis, Skewness Preference, and the Demand for Money', *The American Economic Review*, vol. 62(3), pp. 354–371.

Viscusi, W.K. (1986). 'The Risks and Rewards of Criminal Activity: A Comprehensive Test of Criminal Deterrence', *Journal of Labor Economics*, vol. 4(3), pp. 317–340.

Viscusi, W.K. (1993). 'The Value of Risks to Life and Health', *Journal of Economic Literature*, vol. 31(4), pp. 1912–1946.

Webster, C.M., Doob, A.N. and Zimring, F.E. (2006). 'Proposition 8 and Crime Rates in California: The Case of the Disappearing Deterrent', *Criminology & Public Policy*, vol. 5(3), pp. 417–448.

Weisel, D.L. (2007). 'Bank Robbery', Community Oriented Policing Service, U.S. Department of Justice.

Witte, A.D. (1980). 'Estimating the Economic Model of Crime With Individual Data', *The Quarterly Journal of Economics*, vol. 94(1), pp. 57–84.

Wolpin, K.I. (1978). 'An Economic Analysis of Crime and Punishment in England and Wales, 1894-1967', *The Journal of Political Economy*, vol. 86(5), pp. 815–840.

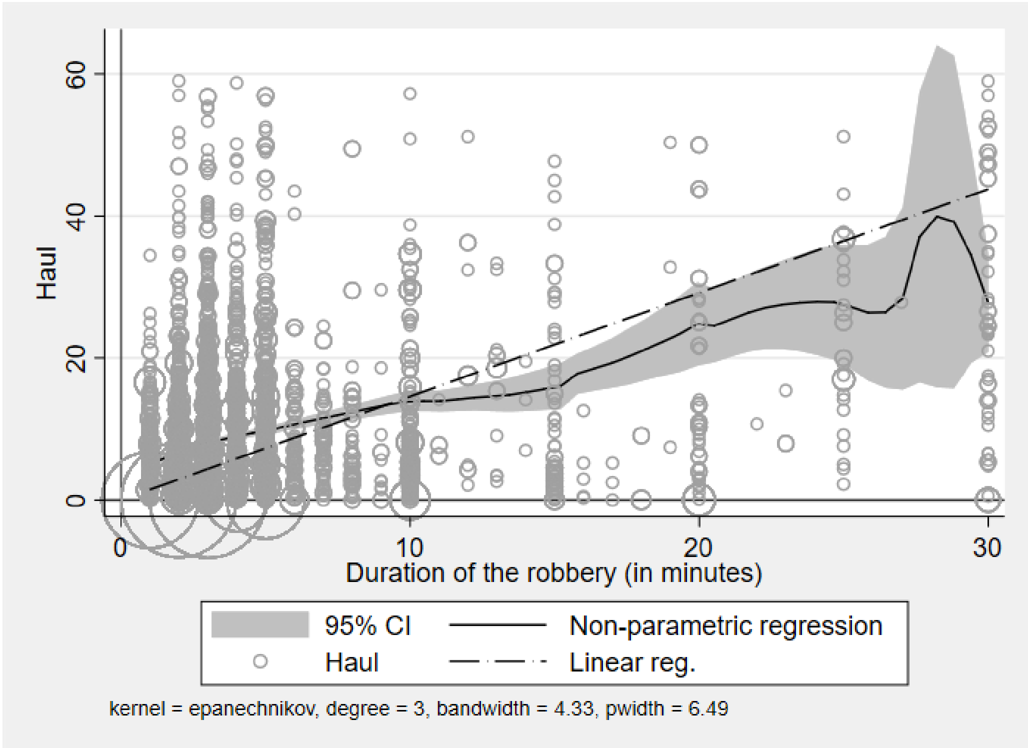

Figure 1: *Haul and Time Spent Inside the Bank*

Notes: The y-axis shows the haul (in €1,000s) and the x-axis shows the duration of the robbery. Circles (proportional to their frequency) show the raw data and are truncated at 60,000€ (97th percentile). The non-parametric fit is based on a locally polynomial regression of degree 3 with asymptotically optimal constant bandwidth (Fan and Gijbels, 1996).

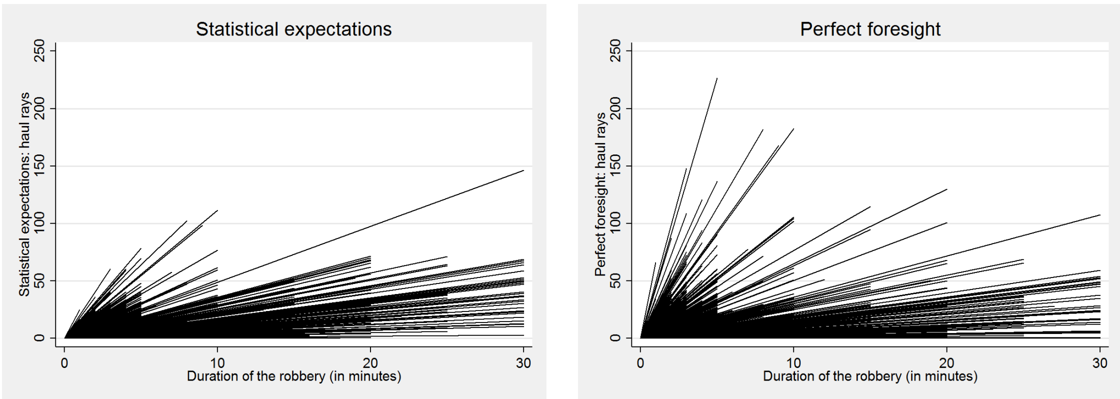

Figure 2: *Predicted Hauls and Marginal Hauls*

Notes: The figure on the right shows the actual realizations of the hauls (the endpoints, Y) connected with the origin (the perfect foresight hypothesis). The slopes of these lines are the predicted marginal hauls, Y/t. The figure on the left shows the same for the expected hauls under the statistical expectations model.

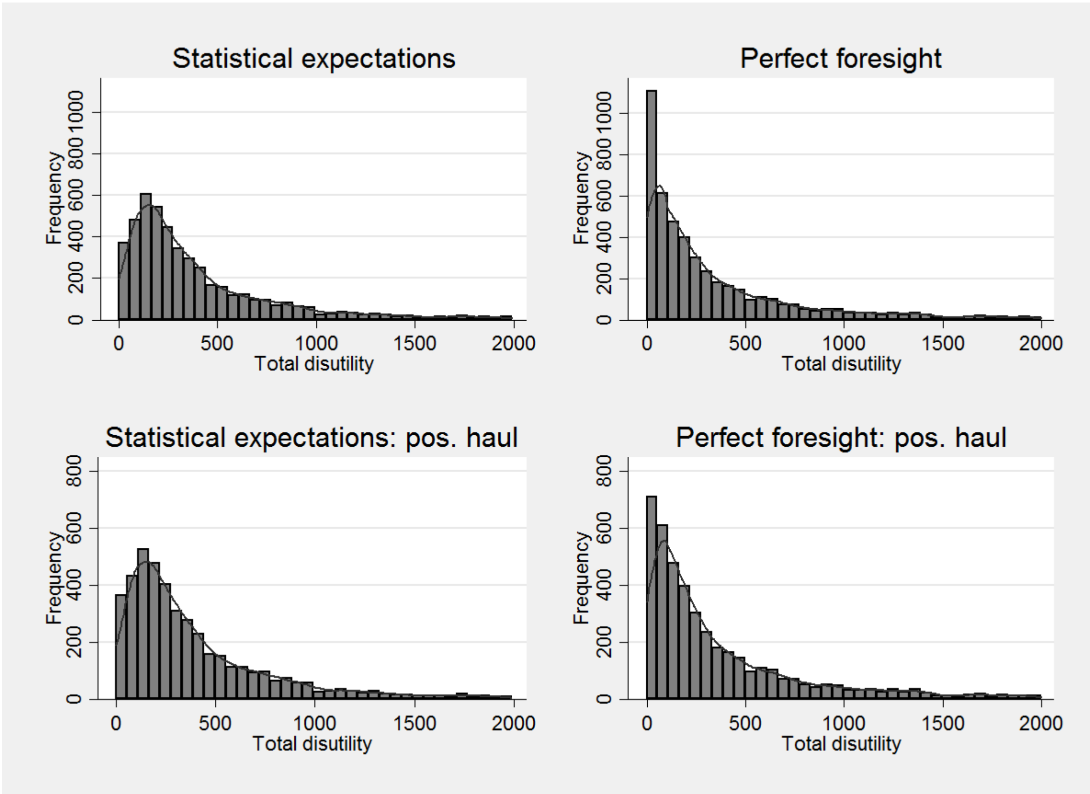

Figure 3: *The Distribution of the Total Disutility of Prison*

Notes: The top two figures show the distribution (capped at €2,000,000) of the total disutility of prison (in €1,000s) for the statistical expectations and perfect foresight models. The bottom two figures exclude observations with zero hauls.

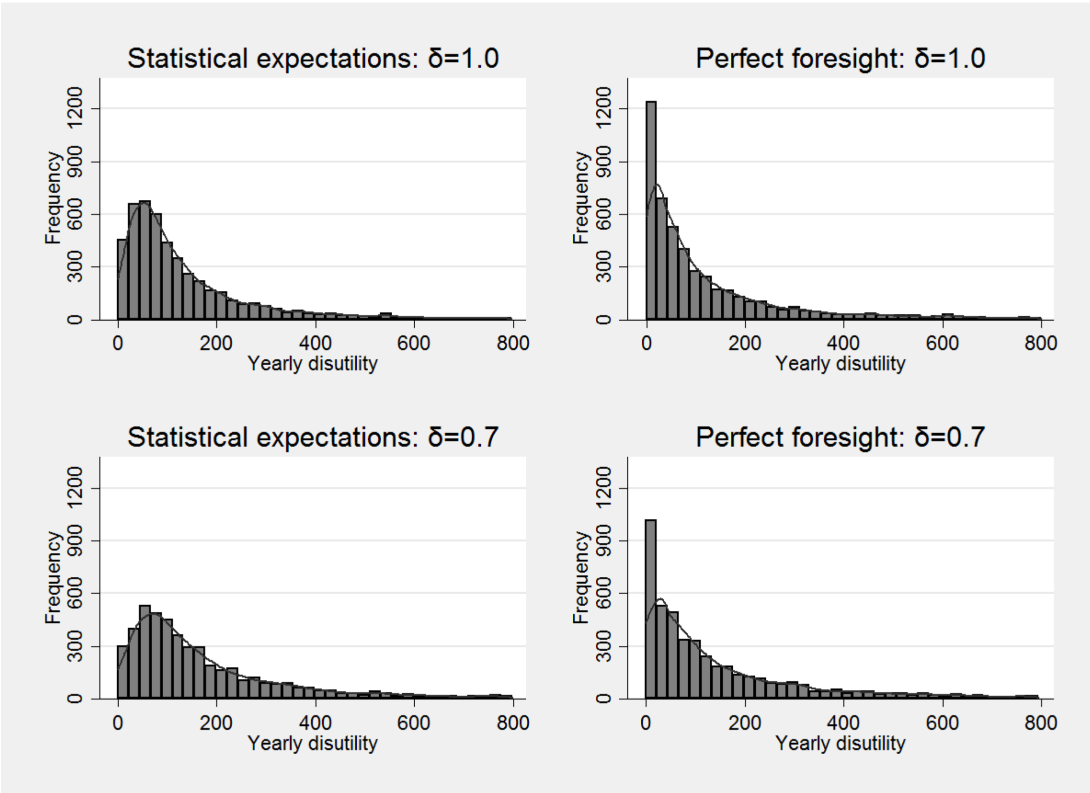

Figure 4: *The Distribution of the Yearly Disutility of Prison*

Notes: The top two figures show the distribution (capped at €800,000) of the yearly disutility of prison (in €1,000s) for the statistical expectations and perfect foresight models. The yearly figures are computed for a predicted sentence length based on the regression shown in column 2 of Table 9, for a discount factor of 1.0. The bottom two figures use a discount factor of 0.7.

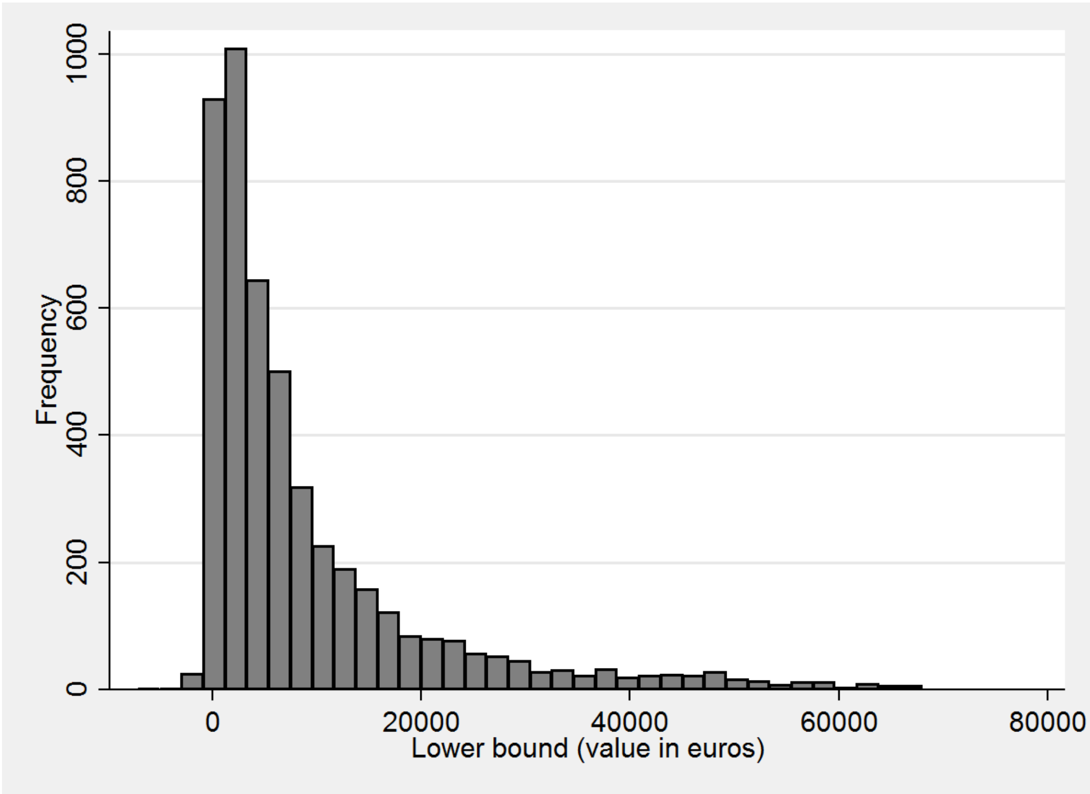

Figure 5: *The Distribution of the Lower Bound of the Fixed Return to Robbery*

Notes: This figure plots the distribution of the implied lower bound on the fixed return to committing a bank robbery.

Table 1: *"Life Table" of Bank Robberies*

Time	Number surviving to time $t-1$	Arrested between $t-1$ and t	Successful between $t-1$ and t	Total
1	4969	20	272	292
2	4677	71	1041	1112
3	3565	101	1597	1698
4	1867	31	485	516
5	1351	51	698	749
6	602	2	73	75
7	527	5	49	54
8	473	1	51	52
9	421	0	12	12
10	409	20	165	185
11	224	0	4	4
12	220	0	9	9
13	211	2	8	10
14	201	0	3	3
15	198	5	44	49
16	149	1	4	5
17	144	1	2	3
18	141	5	0	5
19	136	0	3	3
20	133	9	48	57
22	76	0	1	1
23	75	0	3	3
25	72	0	28	28
27	44	0	1	1
30	43	3	40	43

Notes: This table shows the distribution of successful and unsuccessful bank robberies that last at most half an hour.

Table 2: *Summary Statistics*

	Mean	SD
Arrested	0.066	0.25
Duration of the robbery (in minutes)	4.27	4.17
Total haul	16,009	29,711
Haul per robber	8,732	13,653
Firearms	0.15	0.36
Knife or makeshift weapon	0.70	0.46
Two robbers	0.52	0.50
Three or more robbers	0.15	0.36
Masked robbers	0.43	0.49
Traveling on foot	0.34	0.48
Traveling by car	0.20	0.40
Traveling by motorbike	0.07	0.25
Isolated branch	0.25	0.43
Bank with little cash	0.63	0.48
Bank with less than 5 employees	0.52	0.50
Number of security devices (SD)	5.61	1.18
Average number of characteristics	1.26	0.38
% of invisible devices	0.67	0.16
Guarded	0.08	0.27
Number of employees present	4.80	2.96
Number of customers present	2.81	3.84
Number of customers unknown	0.10	0.31
Before 8am	0.04	0.19
Between 12pm and 3pm	0.31	0.46
Between 3pm and 4pm	0.04	0.20
Monday	0.20	0.40
Tuesday	0.18	0.39
Wednesday	0.18	0.39
Thursday	0.19	0.39
Friday	0.24	0.43
N. obs.	4,969	

Notes: This table shows the summary statistics for the sample of bank robberies that last at most 30 minutes. About 96% of all robberies last at most 30 minutes.

Table 3: *Statistical Expectations Model*

	(1) Positive Haul	(2) (Log) Haul Per Minute	(3) Hazard of Police Arrival	(4) Caught After Exit	(5) Disutility of Prison
Firearms	0.46***	0.25***	-0.19	-0.17	0.53
	(0.10)	(0.07)	(0.31)	(0.15)	(0.34)
Knife or makeshift weapon	0.50***	0.14**	0.42*	-0.10	-0.20
	(0.07)	(0.06)	(0.23)	(0.11)	(0.25)
Two robbers	0.30***	-0.57***	-0.45***	-0.27***	-0.06
	(0.06)	(0.04)	(0.14)	(0.09)	(0.15)
Three or more robbers	0.36***	-0.86***	-0.35*	-0.36**	-0.46**
	(0.10)	(0.06)	(0.20)	(0.15)	(0.22)
Masked robbers	0.06	0.15***	-0.38***	-0.36***	0.55***
	(0.06)	(0.04)	(0.14)	(0.10)	(0.15)
Traveling on foot	-0.02	-0.08*	0.51***	0.22**	-0.62***
	(0.07)	(0.05)	(0.16)	(0.11)	(0.18)
Traveling by car	-0.05	0.11**	0.37**	0.40***	-0.29
	(0.08)	(0.05)	(0.17)	(0.12)	(0.19)
Traveling by motorbike	0.02	-0.12	-0.40	0.47***	0.29
	(0.12)	(0.09)	(0.43)	(0.17)	(0.45)
Isolated branch	0.03	0.03	-0.14	0.07	0.19
	(0.07)	(0.04)	(0.16)	(0.10)	(0.17)
Bank with little cash	-0.16***	-0.04	0.08	0.07	-0.14
	(0.06)	(0.04)	(0.13)	(0.09)	(0.15)
Bank with less than 5 employees	0.10*	-0.27***	-0.40***	0.02	0.16
	(0.06)	(0.05)	(0.14)	(0.09)	(0.16)
Number of security devices (SD)	0.00	-0.04**	-0.04	-0.10***	0.00
	(0.03)	(0.02)	(0.05)	(0.03)	(0.05)
Average number of characteristics per SD	-0.23***	-0.26***	-0.06	0.07	-0.23
	(0.08)	(0.06)	(0.16)	(0.10)	(0.18)
% of invisible devices	-0.37**	-0.67***	-0.22	-0.31	-0.50
	(0.19)	(0.12)	(0.40)	(0.24)	(0.43)
Guarded	-0.13	-0.21***	0.50**	-0.28	-0.76***
	(0.10)	(0.08)	(0.20)	(0.21)	(0.23)
Number of employees present	-0.01	0.03***	0.04**	0.03**	-0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Number of customers present	0.00	-0.01	-0.02	0.02	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Number of customers unknown	-0.25**	0.05	-0.13	0.22	0.14
	(0.10)	(0.07)	(0.24)	(0.14)	(0.26)
Before 8am	-0.63***	0.08	-0.43	0.14	0.37
	(0.12)	(0.11)	(0.34)	(0.23)	(0.38)
Between 12pm and 3pm	-0.11*	-0.12***	-0.26*	-0.01	0.13
	(0.06)	(0.04)	(0.14)	(0.09)	(0.15)
Between 3pm and 4pm†	-0.60***	0.13	-1.70**	–	1.73***
	(0.12)	(0.11)	(0.81)		(0.52)
Monday	0.05	0.17***	-0.02	0.15	0.20
	(0.08)	(0.06)	(0.20)	(0.12)	(0.22)
Tuesday	0.07	0.08	-0.05	-0.11	0.15
	(0.09)	(0.06)	(0.19)	(0.13)	(0.22)
Wednesday	-0.01	-0.02	0.33*	-0.02	-0.36*
	(0.09)	(0.06)	(0.19)	(0.13)	(0.21)
Thursday	-0.03	0.07	0.00	0.07	0.06
	(0.08)	(0.06)	(0.18)	(0.12)	(0.20)
Ability	0.04**	1.02***	-0.14*	-0.14***	1.17***
	(0.02)	(0.05)	(0.07)	(0.05)	(0.10)
Constant	1.49***	8.77***	-4.61***	-1.67***	2.40***
	(0.33)	(0.19)	(0.65)	(0.63)	(0.71)
Standard Deviation of Error	–	0.75***	–	–	0.59***
		(0.08)			(0.03)
Province fixed effects (FE)	Yes	Yes	Yes	Yes	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes
Observations	4969	4969	4969	4969	4969

Notes: † This variable perfectly predicts arrest after exiting the bank. (No arrests were made after robbers exited the bank for robberies that took place between 3pm and 4pm.) Standard errors are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 4: *Perfect Foresight Model*

	(1) Positive Haul	(2) (Log) Haul Per Minute	(3) Hazard of Police Arrival	(4) Caught After Exit	(5) Disutility of Prison
Firearms	0.46***	0.25***	-0.17	-0.14	0.40
	(0.10)	(0.08)	(0.37)	(0.15)	(0.42)
Knife or makeshift weapon	0.50***	0.14**	0.50*	-0.10	-0.44
	(0.07)	(0.06)	(0.26)	(0.11)	(0.29)
Two robbers	0.30***	-0.57***	-0.47***	-0.26***	-0.06
	(0.06)	(0.04)	(0.16)	(0.09)	(0.18)
Three or more robbers	0.36***	-0.86***	-0.33	-0.33**	-0.55**
	(0.09)	(0.06)	(0.22)	(0.15)	(0.27)
Masked robbers	0.06	0.15***	-0.44***	-0.34***	0.63***
	(0.06)	(0.04)	(0.16)	(0.10)	(0.19)
Traveling on foot	-0.02	-0.08*	0.55***	0.21**	-0.71***
	(0.07)	(0.05)	(0.18)	(0.10)	(0.21)
Traveling by car	-0.05	0.11**	0.39*	0.40***	-0.38
	(0.08)	(0.05)	(0.20)	(0.12)	(0.24)
Traveling by motorbike	0.02	-0.12	-0.45	0.49***	0.33
	(0.12)	(0.09)	(0.46)	(0.17)	(0.49)
Isolated branch	0.03	0.03	-0.16	0.07	0.21
	(0.07)	(0.05)	(0.18)	(0.09)	(0.21)
Bank with little cash	-0.16***	-0.04	0.12	0.07	-0.18
	(0.06)	(0.04)	(0.16)	(0.09)	(0.18)
Bank with less than 5 employees	0.10*	-0.27***	-0.40**	0.02	0.17
	(0.06)	(0.05)	(0.16)	(0.09)	(0.19)
Number of security devices (SD)	0.00	-0.04**	-0.06	-0.10***	0.02
	(0.03)	(0.02)	(0.06)	(0.03)	(0.06)
Average number of characteristics per SD	-0.23***	-0.26***	-0.03	0.07	-0.19
	(0.08)	(0.06)	(0.19)	(0.10)	(0.21)
% of invisible devices	-0.37**	-0.67***	-0.15	-0.34	-0.67
	(0.19)	(0.12)	(0.46)	(0.25)	(0.51)
Guarded	-0.13	-0.21***	0.57**	-0.28	-0.84***
	(0.10)	(0.08)	(0.23)	(0.21)	(0.28)
Number of employees present	-0.01	0.03***	0.05**	0.03**	-0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Number of customers present	0.00	-0.01	-0.02	0.02	0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
Number of customers unknown	-0.25**	0.05	-0.12	0.26*	0.16
	(0.10)	(0.07)	(0.28)	(0.14)	(0.31)
Before 8am	-0.63***	0.08	-0.32	0.10	0.41
	(0.12)	(0.11)	(0.40)	(0.23)	(0.47)
Between 12pm and 3pm	-0.11*	-0.12***	-0.23	-0.04	0.11
	(0.06)	(0.04)	(0.16)	(0.09)	(0.20)
Between 3pm and 4pm†	-0.60***	0.13	-1.75*	–	1.98***
	(0.12)	(0.11)	(0.94)		(0.57)
Monday	0.05	0.17***	-0.05	0.15	0.22
	(0.08)	(0.06)	(0.22)	(0.12)	(0.25)
Tuesday	0.07	0.08	-0.04	-0.12	0.12
	(0.09)	(0.06)	(0.23)	(0.14)	(0.26)
Wednesday	-0.01	-0.02	0.35	-0.03	-0.41
	(0.08)	(0.06)	(0.22)	(0.13)	(0.26)
Thursday	-0.03	0.07	0.02	0.05	0.04
	(0.08)	(0.06)	(0.21)	(0.12)	(0.24)
Ability	0.08**	1.18***	-0.20**	-0.13***	1.42***
	(0.04)	(0.03)	(0.09)	(0.05)	(0.11)
Constant	1.49***	8.77***	-4.68***	-1.60**	-1.56
	(0.33)	(0.19)	(0.82)	(0.70)	(0.96)
Standard Deviation of Error	–	0.46***	–	–	6.52***
		(0.02)			(0.18)
Province fixed effects (FE)	Yes	Yes	Yes	Yes	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes
Observations	4969	4969	4969	4969	4969

Notes: † This variable perfectly predicts arrest after exiting the bank. (No arrests were made after robbers exited the bank for robberies that took place between 3pm and 4pm.) Standard errors are reported in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: *Heterogeneity in Estimated Disutilities of Prison*

	CV	P5	P10	P25	P50	P75	P90	P95
				Total disutility				
Statistical expectations	2.25	40.23	70.54	146.19	284.91	584.44	1172.52	1970.97
Perfect foresight	3.63	0.00	4.08	65.78	207.77	558.83	1356.23	2239.39
				Yearly disutility, discount factor of 1.0				
Statistical expectations	2.00	13.53	23.84	48.86	94.51	186.49	373.15	589.40
Perfect foresight	3.13	0.00	1.45	22.26	67.69	180.14	434.94	733.15
				Yearly disutility, discount factor of 0.7				
Statistical expectations	2.10	18.51	32.84	67.28	130.18	262.53	523.96	844.77
Perfect foresight	3.35	0.00	1.93	30.09	94.57	252.38	606.41	1049.66

Notes: This table shows the coefficient of variation (CV), and the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the disutility of prison for the statistical expectations and perfect foresight models. The yearly figures are computed for a predicted sentence length based on the regression shown in column 2 of Table 9.

Table 6: *Percentage Change in Expected Sentence Corresponding to* $t^* = 0$

Percentage of robberies	5%	25%	50%	75%	95%
Statistical expectations, $\delta = 1$	0.00	0.01	0.02	0.03	0.07
Statistical expectations, $\delta = 0.7$	0.01	0.02	0.03	0.06	0.13
Statistical expectations, $\delta = 0.5$	0.02	0.04	0.07	0.11	0.26
Statistical expectations, $\delta = 0.3$	0.05	0.11	0.20	0.35	0.94
Perfect foresight, $\delta = 1$	0.00	0.01	0.02	0.04	0.11
Perfect foresight, $\delta = 0.7$	0.01	0.02	0.04	0.08	0.19
Perfect foresight, $\delta = 0.5$	0.02	0.05	0.08	0.15	0.38
Perfect foresight, $\delta = 0.3$	0.05	0.14	0.25	0.47	1.39

Notes: This table shows the percentage change in the expected sentence needed to drive the duration of x% of robberies to 0. Note that for a discount factor of 1, this number is the same as the percentage increase in total disutility required.

Online Appendix

O1: Comparison of Italy, Europe, and the US

According to the Uniform Crime Statistics, each year in the US there are around 10,000 bank robberies, representing more than 10% of all commercial robberies, with an average haul of 4,000 dollars (Weisel, 2007). Relative to its size, Italy faces a far greater problem. Each year there are more bank robberies in Italy than in the rest of Europe put together–approximately 3,000. Data from the European Banking Federation (covering Europe and a few other countries) reveal that Italy is followed by Canada and Germany, which have around 800 robberies per year, then by France with around 600 (Table 7). The US has more than 5 times the population of Italy but just 3 times as many bank robberies (Weisel, 2007).

Low probabilities of apprehension, large cash holdings, but also mild sentencing and the banks' fears that more stringent security devices would lead to a loss of clients, are believed to be the main drivers of Italy's high number of bank robberies. Furthermore, the trend over time is not wholly encouraging. Figure 6 shows the average haul (right axis) and the number of bank robberies (left axis) between 1990 and 2006. While the average haul went down, the number of bank robberies went from fewer than 1,500 in 1990 to double that number less than 10 years later.

Perceived costs of robbing banks depend on the probability of apprehension and on the expected sanctions. More than 90% of Italian bank robberies end up without an arrest, while in the US 33% of bank robbers are arrested on the same day they commit the robbery. Moreover, US federal guidelines impose sentences of up to 20 years (25 years when a weapon is used), while in Italy the sentence lengths range between 3 and 10 years depending on the severity of the crime. The range becomes 4.5 to 20 years when at least one of the following conditions is satisfied (Art. 628 of the penal code): a weapon is used, the robber uses a disguise, he works in a group, violence is used to incapacitate a victim, or the robber belongs to an organized crime association.

The expected costs of robbing a bank (to the robber) are, therefore, noticeably lower in Italy than in the US. What about the expected costs to society? The average haul is almost €20,000 (in the US it is equivalent to approximately €6,000). This leads to a direct cost on the order of €50 million a year. But the indirect cost is even larger. A survey of 21,000 retail bank branches, representing 65% of all Italian branches, shows that in 2006 banks spent an average of €10,700 per branch to prevent bank robberies (a total of more than €300 million) according to OSSIF (2006). Each branch spent an additional €4,900 to prevent thefts and €6,300 to protect financial couriers. Therefore, the total amount spent by banks in 2006 to prevent thefts and robberies was more than €700 million. This might, in part, explain why Italian banks charge on average the largest account management fees in Europe: €90 against a European average of just €14 (European Commission, 2007). Moreover, Miller-Burke *et al.* (1999) show that in the US most employees have multiple negative health consequences from experiencing a bank robbery while at work, including anxiety and post-traumatic stress disorder. This is unlikely to be very different in Italy and therefore generates an additional cost.

Despite these frightening numbers, there is almost no empirical research in economics and very little research in criminology that has tried to study bank robberies using robbery-level data. One likely reason for this is the lack of such data.

O2: The Expected Sentence Length

As described in the text, there are no official statistics in Italy providing information on sentence lengths that condition on characteristics of the robbery. In order to obtain some information about this, we hand-collected data on each bank robber who was sentenced to prison in the Piedmont region, located in Northern Italy, between 2005 and 2007. For each trial, we manually transcribed data from the official records at the *Tribunale di Torino* (the Court of Turin). We collected data on the sentences given, as well as several characteristics of the associated robberies and the robbers themselves. Table 8 shows the summary statistics for the sample of 324 bank robberies attributed to the 96 different bank robbers sentenced between 2005 and 2007. This implies that in the sample each robber has been convicted for an average of 3.4 bank robberies.

The bank robbers are on average 35 years old, most are Italian (92%), and despite the convictions coming from a Northern region, 35% were born in the south of Italy. Sixty-seven percent of the robbers are recidivists and 33% accept a plea bargain. The other variables vary by robbery. In 22% of the cases robbers use firearms (versus 15% from the Italian Banking Association data), in 57% they wear a mask (versus 43%) and in 69% they work in teams (versus 66%). Four percent of the time the robber takes hostages. The average total haul is €12,406, slightly lower than the average total haul observed in our main data. While the mix of *modus operandi* of robbers that were sentenced in Piedmont is slightly different than in the countrywide robbery data of the Italian Banking Association, the criminal law and, thus, the determinants of the sentence length should be the same for all regions in Italy.

The average sentence length is 3.5 years in prison. Data on sentence durations allow us to model the log-sentence length based on the same *modus operandi* variables observed for the bank robberies in our main dataset. In order to determine the way the *modus operandi* shapes the expected sentence length S, we regress the log-sentence length on whether the robber used firearms, was masked, or worked in a group. Estimates are shown in Table 9. Based on column 1, using a firearm increases the sentence by approximately 39%. Working in groups and wearing a mask have a smaller effect on the sentence. Working in groups increases the sentence length by 20%, and being disguised increases it by less than 10%, but the effect is not statistically different from zero. In column 2, we also control for recidivism, hostages, plea bargain, year, total number of (known) robberies committed, and total haul. The magnitude of the coefficients on firearms, masks, and groups all decrease, with only the use of firearms associated with strong and significant sentencing enhancements. This potentially explains why so many robbers choose to work in groups and to wear a mask, while significantly fewer use a firearm.

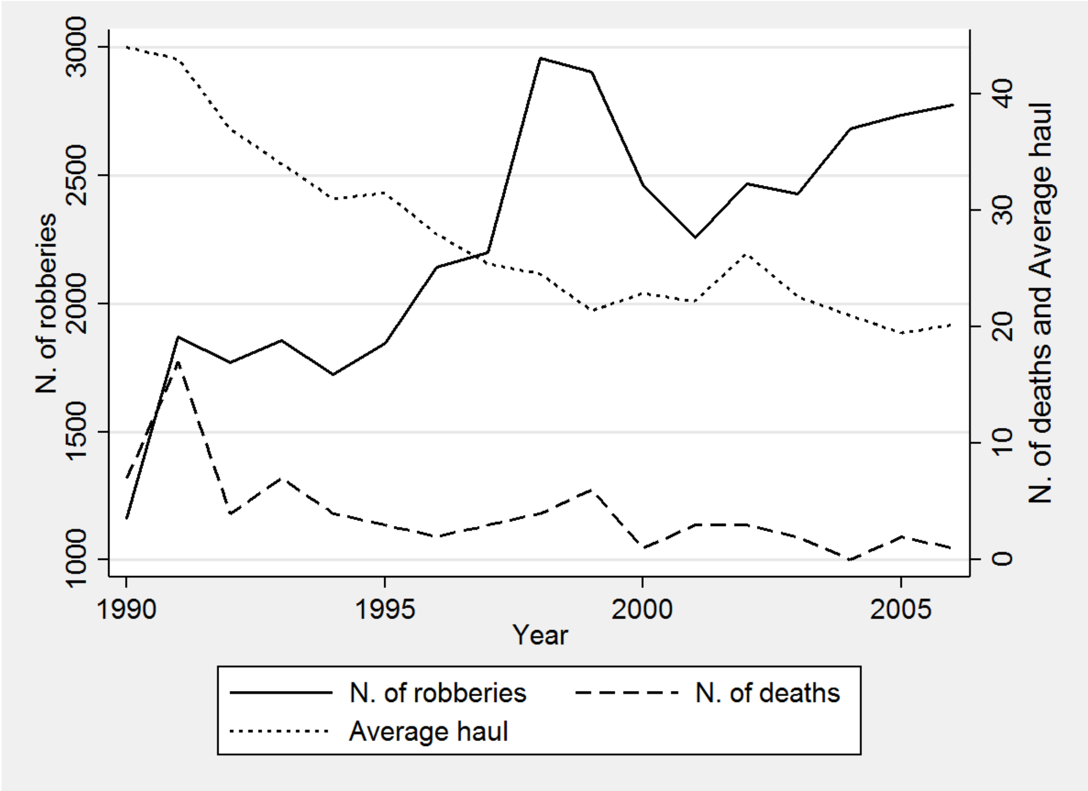

Figure 6: *Number of Italian Bank Robberies, Average Haul, and Number of Casualties*

Notes: This figure shows the total number of Italian bank robberies (left axis), the average haul (in €1,000s) and number of casualties (both on the right axis) between 1990 and 2006.

Table 7: *Number of Bank Robberies Across the World*

	Total Robberies	R. per Branch (in %)		Total Robberies	R. per Branch (in %)
Andorra	0.00	0.00	Japan	133.29	0.98
Australia	119.00	2.54	Liechtenstein	0.00	0.00
Belgium	117.43	1.37	Lithuania	12.29	1.79
Bulgaria	1.00	0.32	Luxembourg	2.14	0.71
Canada	827.71	14.10	Malta	0.71	0.70
Croatia	27.43	2.45	Monaco	0.00	0.00
Cyprus	6.57	0.91	New Zealand	25.14	2.18
Czech Republic	66.29	4.08	Norway	11.86	0.96
Denmark	160.14	7.91	Poland	72.71	0.61
Estonia	1.71	0.69	Portugal	97.29	1.78
Finland	8.71	0.53	Slovak Republic	13.57	1.16
France	639.29	2.28	Slovenia	11.57	1.00
Germany	837.71	1.96	Spain	523.43	1.36
Greece	143.57	3.68	Sweden	38.86	2.00
Hungary	33.29	1.03	Switzerland	16.29	0.43
Iceland	2.71	1.66	The Netherlands	77.14	2.41
Ireland	64.57	5.22	Turkey	83.86	1.22
Italy	2770.86	8.67	UK	191.86	1.74

Source: European Banking Federation. "Total Robberies" are the average yearly number of robberies from 2000 to 2006.

Table 8: *Summary Statistics from Trials Related to Bank Robberies*

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
	Characteristics of bank robbers				
Age	35.774	10.217	18	65	93
Foreigner	0.083	0.278	0	1	96
Southern	0.354	0.481	0	1	96
Number of robberies	3.375	3.363	1	15	96
Recidivist	0.677	0.470	0	1	96
Plea bargain	0.333	0.474	0	1	96
Total sentence	3.458	1.639	1.333	12.667	95
	Characteristics of robberies				
Firearms	0.222	0.416	0	1	324
Masked	0.571	0.496	0	1	324
Group robbery	0.688	0.464	0	1	324
Hostages	0.040	0.197	0	1	324
Total haul	12.406	21.633	0	145	324
Year	2004.901	1.471	1993	2007	323

Notes: These data are based on trials against 96 bank robbers, involved in a total of 324 bank robberies carried out between 1993 and 2007, that were held in the judicial district of Piedmont.

Table 9: *Determinants of the Sentence Length*

	(1)	(2)
	log-Sentence	
Firearms	0.39***	0.28***
	(0.10)	(0.09)
Masked	0.07	0.03
	(0.08)	(0.08)
Group robbery	0.20**	0.09
	(0.08)	(0.08)
Number of robberies		0.03**
		(0.02)
Recidivist		-0.03
		(0.08)
Hostages		-0.10
		(0.18)
Total haul		0.00
		(0.00)
Plea bargain		-0.27***
		(0.08)
Year		-0.02
		(0.02)
Observations	95	94
R-squared	0.197	0.361

Notes: These regressions are based on trials against 96 bank robbers, involved in a total of 324 bank robberies carried out between 1993 and 2007, that were held in the judicial district of Piedmont. Missing data on sentence and year of sentencing cause us to lose one and two observations in columns 1 and 2, respectively. Clustered standard errors (at the province level) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$