Optimizing Behavior During Bank Robberies: Theory and Evidence on the Two Minute Rule*

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Abstract

I use data on individual bank robberies to estimate the distribution of criminals' disutility of jail. The identification rests on the money versus risk trade-off that criminals face when deciding whether to stay an additional minute while robbing the bank. The observed (optimal) duration of successful robberies identifies the individual compensating variation of jail, called disutility of jail. The distribution of the disutility which is often assumed to be degenerate, resembles instead an earnings distribution, and highlights heterogeneity in the response to deterrence. General deterrence effects are increasing in criminal's disutility.

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> "Every second past two minutes increased the odds that a bank robber would be caught. A professional would leave a bank when the clock struck two whether he had the money or not. Lynn Phelps knew these guys were amateurs, dicking around in the bank for nine minutes." ("The Two Minute Rule," Crais, 2007)

1 Introduction

At least since Becker's 1968 seminal paper economists consider that criminal strategies depend on probabilistic expectations about illegal proceeds, risk of failure, and the consequent loss of utility.

But unlike market prices the expectations are not posted, but rather learned from experience or word-of-mouth,[1], while the loss of utility is likely to depend on a variety of unobserved factors (opportunity cost, aversion to jail, family and friends, etc.).

Researchers have been forced to come up with clever ways to test Becker's model. The most convincing crime studies exploit quasi-random changes in either certainty or severity of sanctions, overcoming the data limitations by differencing out what is unobserved.[2] The price to be paid has been to assume that all criminals share the same disutility of jail, and thus are equally deterred.

The main contribution of this paper is to detect potential heterogeneity in such disutility. I show that using any arbitrary utility function, aversion to jail, initial level of wealth, discount rate, as well as sentence length, the disutility can be summarized by an approximated compensating variation.

I then use precise data on about 5,000 individual and fully observable trade-offs faced by Italian bank robbers between 2005 and 2007 to identify criminal's *individual* disutility of jail.[3] The identification of the compensating variation rests on the fact that criminals, after selecting a bank, a weapon, a disguise, and a team, need to choose how much time to spend inside the bank collecting the money. From interviews of robbers it is safe to say that the choice depends on the expected marginal benefits (loot) and expected marginal costs (increased risk of arrest) of staying an additional minute inside the bank (Cook,

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

[2]See Durlauf and Nagin (2010) for an overview on empirical studies on the deterrent effect of imprisonment.

[3]Unless one is willing to impose strong restrictions on the robbers preferences, I show that the individual components of the compensating variation are not identified.

2009).[4]

Information about the robbers' loot and arrest allows me to estimate the robbers' expectations. In line with most the crime literature I assume that criminals' expectations are objective, though I allow them to vary across individuals.[5]

Most crime research deals only with expectations about arrest and conviction, while in this paper I use objective measures of expected criminal proceeds.[6]

Without some measure of monetary trade-off one cannot identify the disutility of jail, an otherwise inherently unobservable entity. This is unfortunate as the disutility shapes general deterrence (see Polinsky and Shavell, 1999, for a theoretical discussion about the importance of the disutility of incarcaretion).[7]

Despite the simplicity of the setup–a closed environment and a unidimensional continuous choice– the identification rests on assumptions about how the expectations are formed. A chosen duration can signal i) different levels of disutility, or ii) different beliefs and belief formation about the trade-offs.

The use of two fundamentally opposite views to measure the trade-off: a) statistical (rational) expectations and b) perfect foresight (expectations), deliver very similar results about the disutility.[8] If robbers have superior information about their own ability that is unobservable to the econometrician, I show that the two methods bound the variability of the disutility of jail.

The two methods produce distributions of the disutility of incarceration that are similar in shape, but different in terms of scale (a tenfold relative difference in standard deviation) and location (a twofold difference in means). Despite these differences, the

[4]The intuition for the identification is that conditional on the expected marginal loot and the expected hazard rate of failure, a criminal with a higher disutility of jail will, typically, choose to spend less time inside the bank branch.

[5]Alternatively researchers have tried to elicit them ex-post, once criminals are in jail. See Polich et al. (1980b) and Loughran et al. (2012) for an early and a recent survey of prison inmates. Manski (2004) advocates the use of elicited subjective expectations to model choice. A few studies have estimated deterrence using individual level data on perceived deterrence (Polich et al., 1980a) or on other self-reported crime data (Grogger, 1998, Glaeser and Sacerdote, 1999). In both, surveys and self-reports, criminal activities might be subject to untruthful reporting or at least to underreporting (Vicusi, 1986). Nagin (1998) and Durlauf and Nagin (2011) survey the hundreds of papers written on deterrence.

[6]Very few crime data, mainly victimization surveys, contain information on the value of stolen goods. But such surveys typically focus on the victims and contain little information about criminal behavior. According to Witte (1980) "New data sets should also make every possible effort to obtain estimates of the expected payoff from illegal activity."

[7]See also Lee and McCrary (2009) for some comparative static results when changing the utility cost to incarceration.

[8]Since risk are not perfectly foreseeable, I will use an alternative method to take unobserved individual heterogeneity in ability into account (see Section 3.2). Section 3 discusses the different ways to measure expectations.

correlation between the individual disutility based on the perfect foresight assumption and the one based on statistical expectations is close to 90 percent. Consequently, several important comparative statics results do not depend on the method used to measure the expectations.

The distribution of disutility of jail time is positively skewed and resembles a "log-normal" earnings distribution. The heterogeneity in disutilities might depend on several factors. I show that the disutility is also related to their opportunity cost of jail time. For example, criminals with higher disutilities are shown to be more likely to target small banks with large cash holdings, and to use a disguise and firearms.

With the distribution of the disutility at hand, one can generate comparative statics results.[9] Since the total disutility of jail depends on the expected sentence length–a longer jail time leads to larger losses in utility–this paper identifies, conditional on discounting (which is not identified), the individual responsiveness to sentencing. Recently, Kessler and Levitt (1999),[10], Drago et al. (2009), Helland and Tabarrok (2007), and Lee and McCrary (2009) exploit random variation in sentencing to estimate general deterrence. Only the last study, which focusses on juveniles, finds little evidence of deterrence. But all these studies estimate *average* deterrence effects. In contrast, I identify individual responsiveness to changes in the disutility of jail.

I show that increasing the disutility of jail leads to significant reductions in criminal behavior, but that small changes in the degree of discounting can lead to large changes in the degree of deterrence. Without knowledge about criminals discount factor this study cannot pin down the deterrence effect of the severity of punishment.[11]

Instead, what can be pinned down is the *relative* responsiveness to severity. Changes are larger among criminals with a higher opportunity cost of spending time in prison. This generates an interesting selection. As sanctions increase the more able criminals are predicted to be the first quit their criminal career. This means that harshening the rather mild sanctions in Italy (the average prison sentence for a bank robbery is between 3 and 4 years, while it is more than 10 years in the United States) would thus be a way to reduce Italy's dramatic number of bank robberies, driving the most able offenders out of the bank robbery business first.[12]

[9]The disutility might also be used to evaluate more comprehensively the cost and benefits of various aspects of the criminal justice system; for example, it is part of the social cost of incarceration (Barbarino and Mastrobuoni, 2014).

[10]The results have been challenged by Webster et al. (2006) and Raphael (2006).

[11]At the average prison sentence (3.4 years), reducing the discount factor from 1 (no discounting) to 80 percent reduces the deterrence effect by 70 percent.

[12]This finding might explain why in the US, where jail sentences for robbing a bank are on average 400

There are only two other papers that estimate some statistic of the disutility of jail.[13] Abrams and Rohlfs (2010) use bail postings, the amounts paid by suspects to be released while on trial, to estimate average disutility of jail for an individual with a specific set of characteristics of the disutility of jail, which the authors call the *Value of Freedom*. The estimated 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." This paper goes beyond estimating the average disutility of jail, backing out its distribution, without having to deal with credit constraints. The second paper, Reilly et al. (2012), estimates an average disutility of jail for British bank robbers that is ten times larger (£33,545). But later I will argue that even this estimate is likely to be biased towards zero.

A few other researchers study robberies (Cook, 2009, 1990, 1987, 1986, 1985), including bank robberies (Federal Bureau of Investigation, 2007, Weisel, 2007, Baumer and Carrington, 1986). But only Hannan (1982) tries to test deterrence explicitly using data on bank robberies and banks' security devices. The major shortcoming of Hannan (1982) is that the adoption of new security devices is likely to be endogenous. The endogeneity concerns in this study depend on the potential unobserved heterogeneity in the expectations (or in ability), which I discuss in Section 3.

1.1 The Data

I have been granted access to the universe of individual bank robberies perpetrated in Italy between 2005 and 2007.[14] Each year branch managers are required to update the characteristics of their branch (security devices, number of employers, etc). Moreover, after each robbery branch managers are required to fill out a form describing the facts (i.e., number of bank robbers, haul, weapons, technique, etc.). The initial number of robberies is 6,434 but 1,215 are excluded because of missing information on either the robbery or the characteristics of the branch. 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 exact timing. Nevertheless, there is evidence of heaping

percent higher, the pool of robbers is considered to be more amateurish than in Italy (Weisel, 2007).

[13] In spirit this paper is also related to the vast literature that tries to estimate 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).

[14] The Online Appendix A.1 shows the evolution of robberies over the last 15 years, and discusses the Italian robberies in comparison to other countries, including the United States.

in the duration of the robberies.[15] Figure 1 plots the distribution and the cumulative distribution of the durations between 1 and 46 minutes. The 46th minute stands for robberies that last more than 45 minutes. There are 185 of them out of 5,219, or 3.54 percent, while almost 90 percent of robberies last at most 9 minutes.[16] The spikes at multiples of 5 show the heaping. Given that there are no observations between 30 and 40 minutes other than at 30, 35, and 40 minutes for the analysis I disregard 4.7 percent of the robberies that last more than 30 minutes.

Table 1 presents the distribution of durations below 30 minutes separated into successful (no arrest) and unsuccessful (arrest) robberies. At time 0 the data start with 4,972 robberies that last less than 30 minutes. 297 last just one minute. Of these 24 lead to an arrest and 273 don't, and are labeled as successful, even if the robbers walk out of the bank empty-handed. After the first minute 4,675 robberies are left, of which 71 lead to an arrest and 1,049 terminate without an arrest, and so on.

The summary statistics in Table 2 show that between 2005 and 2007 only 6.76 percent of bank robbers were arrested after robberies that lasted less than 30 minutes.[17] The typical robbery lasts around 4.32 minutes and leads to a haul of approximately €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 percent of bank robberies involve firearms, as judges sanction their use with increased punishments. 44 percent of all bank robbers mask their face when robbing a bank. 21 percent of bank robberies happen in central Italy, 29 percent in the South and the rest in the North.[18] Bank robbers are more likely to choose banks that have on average smaller amounts of cash, or that are located in less populous areas.

The data set is rich with information about the security devices installed in the bank. I summarize this information by counting the number of different devices that each bank has, and compute how many characteristics these devices have on average for each bank. For example, 92 percent of the banks have a security entrance but the characteristics differ widely. Some have metal detectors, some have a double door where people can be trapped, some have a biometric sensor, etc., while some entrances might display all

[15] While the heaping might in principle be driven by "rule of thumb" choices of bounded-rational robbers, I believe it is more likely that some managers approximate the duration of the robbery.

[16] Focussing on just these very quick robberies leads to very similar results.

[17] Fifty-nine percent of these arrests are *in flagrante delicto*, during the bank robbery, while the rest happens afterwards. When I exclude the robberies where the arrests do not happen immediately, due to the resulting smaller hazard rates of arrest the estimated disutilities are larger, but all the results are qualitatively similar.

[18] The following central regions separate the southern regions from the Northern ones: Lazio, Marche, Toscana, Molise, and Umbria.

these characteristics. Robbed banks tend to have more security devices installed than the average bank (7.2 versus 6.7), and these devices tend to have more characteristics per device. Banks tend to install new devices after they experience a bank robbery. The majority of these devices are not visible to the criminal (like automatic banknote distributors, banknote spotters, time-delayers, banknote tracing devices, vaults, and alarm systems) while 32 percent are clearly visible (metal detectors, vault's time-locks, and protected teller's post).[19] The last 4 columns of Table 2 allow a comparison between the summary statistics of robberies that last more or less than the median, which is equal to 3 minutes. The average duration of robberies is 2.44 minutes for those that last less than 3 minutes and 7.4 minutes for those the last more than 3 minutes. This difference translates into slightly larger probabilities of arrest 6.28 vs. 7.54 percent, but considerably larger hauls, €11,559 versus €23,269. These differences can in part be explained by differences in the *modus operandi*. Longer robberies are more likely to be operated by teams (77 versus 62 percent), and in longer operations robbers are more likely to be using a firearm (20 versus 12 percent).[20] The other observable characteristics of branches show only minor differences based on the duration of the robberies.

The data that were provided by the Italian Banking Association do not contain any information about the robbers.[21]

2 A Continuous Time Model of Crime

Bank robbers face a trade-off: the longer they stay inside the bank the more money they are able to collect, but the risk of getting caught goes up as well.[22]

The trade-off allows me to identify the criminal's disutility of jail. Conditional on having chosen to rob a bank, the criminal's expected utility $V(t)$ is a function of the duration of the bank robbery. It is also going to be a function of the criminal's initial wealth (W), discount factor (δ), risk aversion (r), as well as the trade-off between loot

[19]Since visible and invisible devices might have a different impact on the robbery in the regressions I will control for the fraction of invisible devices.

[20]Given that the *modus operandi* is likely to influence not only the duration but also the probability of success and the expected haul, it is important to control for it when I model the bank robbers' decision about the duration of the bank robbery.

[21]But it should be noted that such information would come from arrested robbers and thus likely be biased because of selection. In order to have some information about typical sentences I also collected judiciary level data on 95 bank robbers that were sentenced to jail in the judicial district of Turin, a city in Northern Italy (more on this in Section A.2). Unfortunately the judiciary level data does not provide enough detail about the robberies to link them to the robbery data.

[22]Later I show evidence on the positive relationship between the duration of the robbery and the total haul (Figure 2), and on the increased risk (Figure 3).

and risk, which is going to depend on his own ability, as well as on the characteristics of the chosen bank branch, both of which are predetermined once he starts the robbery.[23] More than two thirds of sentenced robbers are "legally speaking" recidivists (have been sentenced before), and most likely an even larger fraction has robbed several businesses before.[24]Based on the experience of most robbers, they should have expectations about cost and benefits of robbing a bank, and are likely to face the following problem:

$$\max_t V(t) = [1 - P(T < t)]E\left[U\left(W + Y(t), 0, r, \delta\right)\right] + P(T < t)U\left(W, C(S), r, \delta\right). \qquad (1)$$

$P(T < t) = F(t)$ represents the probability of apprehension before time t. The random variable T defines the two states of the world, arrest $T < t$ and no arrest $T \geq t$). $E[U\left(W + Y(t), 0, r, \delta\right)]$ is the expected utility from a haul after t minutes ($Y(t)$), while $C(S)$ represents the cost of incarceration with a sentence equal to S (in monetary terms, and over which there is no uncertainty). Notice that for each *individual* U can be any *arbitrary present discounted utility* that depends on streams of consumption, leisure, and prison time (as well as on the preference parameters).

Later, when trying to establish some facts about risk aversion, I will assume preferences that are additively separable over time and that can be represented by constant relative risk aversion (CRRA) utility functions.

Conditional on the robber's expectations about $Y(t)$ and $F(t)$, different observed durations could be driven by heterogeneity in W, r, δ, and $C(S)$. It is convenient to simplify this rather general formulation of the robbers maximization problem without imposing to many restriction on the utility function $U(\cdot)$).

Given that most robbers stay only a few minutes inside the bank, let me approximate the utility they get at the very beginning of their criminal act using a first order Taylor approximation around $t = 0$.[25] This implicitly assumes that robbers care about the expected haul but not about its uncertainty, while they still care about the uncertainty related to the risk of having to pay the cost of incarceration $C(S)$. This assumption,

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

[24]In robberies against businesses in the city of Milan, the police tries to identify offenders across robberies using surveillance cameras and victim reports. Based on such data, 70 percent of robberies are performed by recurrent offenders (Mastrobuoni, 2012).

[25]The approximation is $U\left(W + Y(t), r, \delta\right) \approx U\left(W, r, \delta\right) + \frac{\partial U(W,0,r,\delta)}{\partial W} Y'\left(t\right) t$, where $Y' = \frac{\partial Y}{\partial t}$ and I assumed that at at time 0 the haul is 0, or $Y\left(0\right)$.

With the approximation, the robber's problem becomes

$$\max_t [1 - F(t)]E[Y'(t)]t - F(t)D,$$
$$D = [U(W, r, \delta) - U(W, C(S), r, \delta)]\frac{\partial W}{\partial U(W, 0, r, \delta)} \tag{2}$$

The last term, which I will define as the disutility of jail, $D = D(W, C(S), r, \delta)$, measures (in monetary terms) the utility change when incarceration hits, and can be interpreted as a first order approximation of the compensating variation. Notice that the approximation accommodates any arbitrary utility function. In other words, different robbers may have completely different utility functions.

All the arguments of D introduce potential heterogeneity in the observed behavior of robbers. They may appear to be more reckless (lower D) either because they are liquidity constraint (low W), they do not fear risk r, they do not fear jail time (low $C(\cdot)$), they use a *modus operandi* that minimizes jail time S, or, finally, because they do not care about the future (low δ). While for each successful robber D is identified without imposing any restrictions on the preferences (U, r, δ , etc.), the preferences themselves are not.[26]

All of this heterogeneity, as well as the resulting disutility from jail are unobserved by the econometrician. Given that robbers expect positive net benefits one could estimate an upper bound of $\underline{D}$ setting Eq. 2 equal to zero and solving for the disutility. Reilly et al. (2012) relate the average haul of British bank robberies ($\overline{Y}$) to the overall likelihood of arrest ($\overline{P}$): $\underline{D} = \overline{Y}(1-\overline{P})/\overline{P}$. Applying the same calculation to the Italian bank robberies leads to an estimate for $\underline{D}$ of €119,860. But the bound can be seriously biased, as the average ratio is not equal to the ratio of averages.[27]

Having data on the duration allows me to go beyond estimating an overall average. The optimal duration of a bank robbery t^* is determined when costs and benefits of staying an additional minute equal each other, or $-F'(t^*)[E[Y'(t^*)]t^* + D] + [1 - F(t^*)]E[Y'(t^*) + Y''(t^*)t^*] = 0$.[28] Later, I show that the expected haul appears to be linear (and the marginal haul constant), so that $Y''(t^*) = 0$.

[26] This is not uncommon, as most structural models are only parametrically identified (see, for example, Rust, 1994).

[27] Assuming there are two groups of robbers of equal size with the same expected haul $\overline{Y}$ (£8,000, as in Reilly et al. (2012)) but different expected risk of being caught $\overline{P}$, 10 percent and 30 percent (the average risk is 20 percent, as in Reilly et al. (2012)). The ratio of averages leads to an estimate of $\underline{D}$ equal to $£32,000$, while the average ratio is $£8,000 \times (0.7/0.3 + 0.9/0.1)/2 = £45,333$. Heterogeneity in Y would further increase the difference between the ratio of averages and the average of ratios.

[28] Here and throughout the paper I assume that conditional on entering the bank robbers are going to chose an interior solution, and that the objective function is differentiable.

At this point one can solve the first order condition for the unobserved disutility of jail D,

$$D = \frac{1}{\lambda(t^*)} E[Y'(t^*)] - E[Y'(t^*)]t^*, \tag{3}$$

which conditional on t^* is observed through the individual expectations related to the loot $E(\cdot)$ and the hazard rate $\lambda(t^*) = \frac{F'(t^*)}{1-F(t^*)}$. Thus, a chosen optimal duration t^* identifies the robber's disutility D.

What if after a successful robbery offenders know that with some probability ψ that does not depend on the duration t they risk an arrest? Then one can show that if the loot is recovered the first order condition remains unchanged, while if it is not, the new disutility is proportional to the previous one D ($D_\psi = \frac{1}{1-\psi} D$).[29] It follows that the results are quite robust to arrests that happen independently on t that may not be recorded by the Italian Banking Association. Fifty-nine percent of the arrests are *in flagrante delicto*; the remaining arrests happen afterwards, but might still be related to the duration of the robbery if more time inside the bank premises increases the chances that a security camera captures a glimpse of the perpetrators.

3 Criminals' Expectations

In order to derive the disutility of incarceration one needs estimates of the marginal haul $E[y(t^*)] = E[Y'(t^*)]$, and on the hazard rate of apprehension $\lambda(t^*)$. The next step is to devise an empirical strategy to estimate these functions. As mentioned in the introduction (Section 1) I will use objective measures of individual expectations. Criminals have been shown to have expectations about cost of benefits of their actions. Robbers will have expectations about how much money they gather every minute and expectations about the inherent risk. These two expectations are likely to depend on the perpetrators' past experience, on their ability, on the chosen target and might also be related.

Let us start by discussing the marginal haul, y. A realization y_i for offender i can be thought of as the sum of two random variables: what he was expecting ($\widehat{y}_i^*$) and what turned out to be unexpected (ϵ_i^*); from now on unobserved variables are denoted with a star *. It is hard to say whether such expectations are updated during the short time robbers spend inside the bank. In principle an offender might start his robbery with

[29] In short notation the problem becomes $Y(1-F) - D(F + (1-F)\psi)$ if the robber secures the haul, or $Y(1-F)(1-\psi) - D(F + (1-F)\psi)$ otherwise.

some expectations, and update them as he spends time inside the bank. He might be lucky and tellers have plenty of cash, beyond what he expected given, for example, the branch's typical amount of cash. If robbers are able to quickly update at which speed they are collecting the money, the expected haul is going to be equal to the realized one. Otherwise, robbers are going to stick with their prior belief.

In line with the literature on expectations I call these two extreme scenarios:

1. perfect foresight (perfect expectations), so that the individual expectations are simply the individual realizations (denoted by a $\widetilde{tilde}$); in other words $\epsilon_i^* = 0$;[30]

2. statistical or rational expectations (denoted by a $\widehat{hat}$, so that robbers who look alike in terms of *modus operandi* are assumed to have similar prior expectations that are never updated inside the bank branch during the robbery.[31]

Any unobserved heterogeneity in ability will be fully captured when using perfect expectations, but not when using statistical expectation. Whenever the true expectations are not perfect and contain unobserved heterogeneity, it is easy to show that the variance of the true expectations $\widehat{y_i^*}$ is bound by the variance of the $\widehat{y_i}$ and $\widetilde{y_i}$ (and the mean will be the same).[32]

Each of the two models of expectations has its own advantages and disadvantages. If robbers are coolheaded, the second strategy might become more reasonable as time passes. While the two strategies do not lead to radically different results, later I show that one can combine the two strategy into a learning model, where as time passes expectations are more and more based on the actual loot that robbers end up seizing.

Unlike for the haul, there are only a few signals that change risk perceptions over time. The most important signal is likely to be the arrival of a police patrol, but by then it is also usually too late to change strategy. Moreover, realized risk does not change continuously (one is either apprehended or not), meaning that one cannot use realizations to approximate perceptions. For this reason I specify a parametric function to model risk. Given that there is information on the marginal loot secured by arrested robbers, one can use the realized loot to control for unobserved ability shown in money gathering (assuming the two abilities are proportional to each other).

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

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

[32]Unobserved heterogeneity can be interpreted as a measurement error term that is orthogonal to $\widehat{y_i}$, $\eta_i = \widehat{y}_i^* - \widehat{y}_i$. If $Var(\epsilon^*) > 0$, it follows that $Var(y_i) > Var(\widehat{y_i^*}) > Var(\widehat{y_i})$.

3.1 Statistical Expectations and Perfect Foresight

Figure 2 shows the raw data together with parametric and non-parametric regression lines. Circles are proportional to the number of robberies with particular haul 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 that does not cross the origin corresponds to a simple linear regression.

The unconstrained linear fit is well within the 95 percent confidence interval of the non-parametric fit, suggesting that at least the cross-sectional relationship between the total haul and the duration of the robbery is close to linear.[33] Without observing individual minute-by-minute money gathering it is impossible to ascertain whether such linearity would be preserved at the individual level. Still, a linear technology seems to be consistent with the typical actions taken by the offenders: i) enter the bank and walk to the teller, which usually takes 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 all 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.[34]

Since heaping will introduce some measurement error in duration (see Figure 1) the slopes of these lines are likely to be biased toward zero, thus biasing the intercept away from zero. The dashed line that constraints the regression line to pass through the origin, meaning at at 0 minutes no haul has yet been gathered, has a steeper slope.

The slope of the linear fit is approximately equal to €800 per minute, while the slope when the fit is forced to pass through the origin is close to €1400, a 40 percent relative difference. It can be shown that heaping explains between 10 and 12.5 percent of the relative difference in slopes.[35] There additional bias is likely driven by selection: more

[33] Both a quadratic and a cubic relationship between haul and duration are rejected in favor of the linear one (p-value 0.26 and 0.21, regression results are available upon request). Moreover, the Online Figure 9 shows that fit is similar when controlling for other variables.

[34] Since 95 percent of total hauls are below €55,700, it is also very unlikely that tellers run out of cash, and that the optimal duration t is not based on a marginal trade-off. Even if some tellers do run out of cash at time $\widetilde{t}$, one can show that $\widetilde{t}$ together with the expectations on risk and haul evaluated at $\widetilde{t}$ identify a lower bound of the disutility of jail D. An instant before the teller runs out of money the robber's marginal benefit of staying one more minute inside the bank is larger than the corresponding marginal cost. Changing the equality sign with the inequality sign in the model's first order condition, it follows that the disutility is at least as large as the one based on Eq. 3: $D \leq \frac{1}{\lambda(\widetilde{t})} E[y(\widetilde{t})] - E[y(\widetilde{t})]\widetilde{t}$.

[35] One can show this by redistributing the excess mass at multiples of 5 minutes in duration as was shown in Figure 8. Adding integers that are randomly distributed between -4 and 4 to all durations

productive robbers gather more money per minute, and so might be overly represented around shorter durations. This drives up the haul at short durations and down at longer ones.

In order to avoid these biases, instead of modeling the total haul (Y) as a linear function of the duration t, I model the average haul ($y = Y/t$). Since $Y(0) = 0$ and Y is linear in t the average haul equals the marginal one.[36]

Figure 4 compares the the perfect foresight (left) and the statistical expectations (right) of $y = Y/t$ conditional on *Firearms, Two robbers, Three or more robbers, Masked robbers, Center Italy, Southern Italy, Guarded, Isolated branch, Bank with little cash, Bank with less than 5 employees, Number of Security Devices, Average Number of Characteristics, and % of invisible devices.* In particular I use the predicted values $\widehat{y_i} = \widehat{\alpha} + \widehat{\beta}' x_i$ based on Table 3.[37] The slope of the rays represent the marginal hauls.

The variation in slopes for the perfect foresight model is considerable and likely overstates the true variation in robbers' expectations. For example, several marginal hauls are extremely low or even zero even though no arrest has been made and are unlikely to represent the true individual expectations.

Using statistical expectations one reduces such variance considerably, possibly too much (see the righthand Panel of Figure 4). This is why the two methods generate an upper and a lower bound of the true heterogeneity in expectations. All the results that follow will be organized based on the two alternative ways to measure expectations.

Notice that the purpose of this equation is to provide the best approximation to the individual expectation of the haul. The coefficients on the regressors cannot be given any causal interpretation. Indeed, as outlined in the model, they are supposed to capture individual heterogeneity.

Table 3 presents the estimates of the coefficients from a linear model of $y = Y/t$. The first column controls for part of the *modus operandi.* The baseline robber acts on his own, without a disguise, and does not use a firearm, but rather knives, syringes, or even just a note. Each additional minute spent inside the bank is associated with €3,110 increase

that are multiples of 5 the variance of the measurement error that is driven by heaping is around 0.8, by comparison the variance of the "smoothed" duration is between 15 and 20, depending on how one deals with the endpoints. For brevity these results are not shown, but are available upon request.

[36]In others words, I start with the following model $Y = \alpha + y \times t + \epsilon \times t$, setting $\alpha = 0$ (a normalization that is similar to the zero inputs zero output condition in industrial organization). Dividing by t one can estimate $Y/t = y + \epsilon$. In a previous version of this paper I was modelling the total haul instead of the marginal haul, adjusting for measurement error in the duration t.

[37]Using a more non-parametric approach, for example cell-averages based on the same variables x, the variance in expectations lies in between the one obtained using predicted values and realizations. The results are qualitatively the same no matter how one tries to measure statistical expectations.

in the haul Y (the constant term). Using firearms is associated with larger marginal hauls (+€714), and so is being disguised (+€572). Both are likely signals of ability and professionalism. Operating in groups, instead, seems to be associated with lower the per-capita marginal hauls.

Column 2 adds additional characteristics of the bank to describe the *modus operandi*. Marginal hauls are lower in Northern Italy, in banks with lower cash holdings, and in banks with fewer employees. Having more security devices, security devices with more features, and a security guard is also associated with lower marginal hauls. The geographic isolation as well as the fraction of invisible security devices does not seem to be associated with marginal hauls. The estimated expected haul is simply $\widehat{y} = \widehat{\alpha} + \widehat{\beta}' x_i$ times the observed (and optimal) duration of the bank robbery t^*.[38]

3.2 The Hazard Rate of Arrest

The payoffs from a bank robbery are only part of the story. Criminals are sometimes arrested, and might serve prison time. Figure 3 shows the estimated unconditional hazard rate, $\widehat{\lambda}(t)$, using the exponential hazard model and Cox's proportional hazard model.[39] The reason I focus on the exponential model is to avoid "aiming at a moving target." If the estimated hazard rates differ across time due to selection on ability, it is impossible to pinpoint the criminals' expected marginal cost for each additional minute spent inside the bank. Cox's estimates are subject to selection, but are shown to compare with the more constrained estimates based on the exponential model. While I focus on the exponential model and the non-parametric Cox model, any hazard model leads to very similar results.

Table 4 shows how the same regressors that I used for $E(y(t))$ are associated with $\lambda(t)$ based on both the exponential (Column 1) and Cox's proportional hazard model (Column 3). In the Cox model the coefficients do not depend on the baseline hazard, but the results that follow are quite similar when a constant baseline hazard is used. The reason is that most of the action is due to the way the regressors shift the hazard rates up or down. Criminals who use firearms are less likely to get arrested, and so are robbers who work in groups. This is probably because robbers who work in groups are likely to monitor the streets and realize possible dangers. As before, some of the effects might be driven by selection. For example, the number of security devices has a puzzling negative effect.

[38] The Online Appendix Table 10 show that the results are very similar when excluding those robberies where the haul is equal to 0.

[39] In Table 1 and in the hazard models robberies that end without an arrest are treated as censored. Notice that the purpose is again to get the best predictor of the hazard rate and not to infer causality.

This is probably because more able robbers are more likely to target more "challenging" banks, but are also more likely to be successful. The geographic region does not influence the hazard, while smaller and more isolated banks tend to be less risky. Conditional on the other covariates, whether or not the bank has a guard does not seem to matter.

Columns 2 and 4 add the residual of the marginal haul regression to control for unobserved heterogeneity.[40] The implied (non-testable) assumption is that after controlling for observed characteristics, unobserved ability in money gathering and the one in avoiding an arrest are proportional to each other.

The coefficient on the error term is negative for both models, but is only significant when the baseline hazard is forced to be constant. Controlling for unobserved ability in money gathering changes the remaining coefficients very little.[41]

4 The Disutility of Jail

Observing the robbers' optimal decision t^*, the estimates of $E(y(t^*, x))$, and $\lambda(t^*, x)$ allow one to identify the disutility of jail D.[42] In particular, using Eq. 3 with statistical expectations, the estimated disutilities are:

$$\widehat{D}_i = (\widehat{\alpha} + \widehat{\beta}' x_i) \left(\frac{1}{e^{\widehat{\mu} + \widehat{\gamma}_h'(x_i \epsilon_i)}} - t_i^* \right). \quad (4)$$

All estimates are based on hazard rates that control for unobserved heterogeneity in expectations (the residual in the marginal haul regression), though leaving out such control does not alter the results substantially.[43]

Alternatively, when the actual realizations of the haul, as opposed to the statistical

[40]Given the linearity of the previous model this is equivalent to controlling for the realized haul. It is important that arrest does influences the haul only by interrupting the robbery, in other words, one has to assume that the system of two equations (marginal loot and risk) is triangular. The fact that 74 percent of the arrested robbers show a positive loot is evidence in favor of this assumption.

[41]As a note, an exponential hazard model with random gamma distributed unobserved heterogeneity that is assumed to be independent of the *modus operandi* x is rejected by the data in favor of no heterogeneity. Therefore, allowing for random effects also leaves the coefficients on the *modus operandi* x basically unchanged.

[42]Later, in Section 4.2, I will assume that all robbers have a CRRA utility function with different aversion to risk and jail.

[43]Whenever the Cox hazard model is used the hazard rate depends also on t^*, and the results are shown n the Online Appendix A.

predictions, are used to measure criminals' expectations, the disutilities are equal to:

$$\widetilde{D}_i = y_i \left(\frac{1}{e^{\widehat{\mu}+\widehat{\gamma}'_h(x_i\epsilon_i)}} - t^*_i \right). \tag{5}$$

A linear combination of (4) and (5) gives rise to a third estimate. It is plausible to think that robbers enter the bank with some expectations that are based on their prior experience and that only as time passes they update their prior. In such a learning model the predictions and thus the estimated disutilities lie in between the statistical and perfect-foresight ones. At the beginning of the robbery criminals' expectations about the haul depend on their initial prior (based on the statistical model), but as time passes they update their expectations based on the amount of haul they collect (Anwar and Loughran, 2011, find evidence of Bayesian updating among a longitudinal sample of serious juvenile offenders). Assuming that the first-minute prior is later treated as if it was an initial observation, as time passes, more and more weight (in proportion to time) is given to the actual realization. Such algorithm, which has been called the "least squares learning algorithm,[44]" the disutility becomes

$$\overline{D}_i = \frac{\omega}{t^*_i}\widehat{D}_i + \left(1 - \frac{\omega}{t^*_i}\right)\widetilde{D}_i,, \tag{6}$$

meaning that the estimate based on the realizations receives a weight of $1/2\omega$ after the first minute, $2/3\omega$ after the second and so on.

Before displaying the distributions of $\widehat{D}$, notice that this *total* disutility is going to depend on the number of years robbers expect to spend in jail if arrested. It is difficult to tell how criminals discount jail time, and the data do not allow me to estimate such a function. The simplest scenario is that robbers do not discount future jail time at all, and that the total disutility D is time-separable: $D = d \times S$. If robbers discount their future disutility of jail at rate δ, then $D = \sum_{t=0}^{S-1} \delta^t d = d\frac{1-\delta^S}{1-\delta}$.

In Italy there are no official statistics on prison time served by convicted bank robbers that contain data on the *modus operandi*. In order to compute d, the "yearly" disutility of jail, I collected data on sentences related to bank robberies. The data refer to 96 bank robbers convicted in the Piedmont region. Because of lack of information about the targeted branches the corresponding 323 bank robberies, committed between 1993 and 2007, cannot be linked to the robberies outlined in the previous data. The data as

[44]These learning algorithms are good approximations of more complicated Bayesian learning algorithms (Cogley and Sargent, 2008).

well as the process which involves assigning a potential sentence length S to each robbery is discussed in the Online Appendix. The average sentence length is 3.5 years[45], and increases by between 40 percent when robbers use firearms, by 20 percent when they operate in group, and by 7 percent when they use a masquerade.

4.1 The Total and the Yearly Disutility of Jail

Figure 5 shows the distribution of the parametric total disutility (capped at €600,000), for those criminals who were not arrested, and whose choice of t was more likely to be the optimally chosen one t^*. The yearly figures (d) are estimated dividing the total disutility (D) by the predicted sentence length (S).[46]. An interesting feature of all the estimated distributions is the shape: the log-normal shape resembles the typical shape of legitimate earnings. Since the value of staying out of jail is likely to depend on the robbers' earnings potential, it seems that these potential earnings are distributed like the legitimate counterparts. It is worth stressing that nothing in the model prevents the shape of the distribution from taking any other form or from generating negative "values of freedom." The reason is that in Equations 4 and 5 the inverse of the hazard rates is always larger than the chosen t^* (and the predicted marginal hauls are never negative).

Table 5 also shows that the distribution is highly right-skewed. As a consequence, the median is small compared to the mean: €155,000 against €216,000 for the disutility based on the exponential hazard model.[47] The corresponding figures for the yearly disutility are €51,000 and €65,000. These figures are implicitly assuming that robbers do not discount time. If they did, the yearly figures would be relatively larger by $\log S - \log(\frac{1-\delta^S}{1-\delta})$, which for an average sentence of 3.4 years would be less than a quarter with a discount factor of 80 percent, and around 12 percent with a discount factor of 90 percent. Unobserved heterogeneity in discount rates might thus drive some of the heterogeneity in D.

In line with the evidence shown in Figure 4, the estimated disutilities that are based on the perfect foresight assumption and contain the unobserved heterogeneity in expectations lead to considerably larger variances in total disutilities compared to those found under statistical expectations (see Table 5). Compared to the disutilities that are based on statistical expectations, their standard deviation that is more than ten times larger. They also have lower medians and higher means. Moreover, the mass of robbers with zero

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

[46]See the Online Table 12

[47]All the robustness results based on the Cox proportional model are very similar and can be found in the Online Appendix.

realized hauls generate a mass of zero disutilities. Despite such differences the correlation between the two disutilities is 89.77 percent.

Given the very short durations of robberies, the estimates of D based on the learning model tend to be closer to the disutilities based on the statistical estimates of expectations (right-hand panel of Figure 6). The distribution is still unimodal and with a log-normal shape. A final way to combine the two disutility estimates (statistical expectations and perfect foresight) is to view them as upper and lower bounds of $\widehat{D}$. Assigning the same weight to each point within the interval (uniform distribution) and the same weight to each interval (no matter the length), one can build a histogram of such intervals (left-hand panel of Figure 6). Due to the high correlation between the two bounds, the histogram of these intervals has only slightly thicker tails compared to the one based on the learning model.

Summing up, no matter which model is chosen to proxy the robbers' expectations about the haul, and regardless of how one combines the models' uncertainty, the shape of the distribution of the total disutility of jail changes very little. The same is not true about the location and the scale of the distribution. Assuming perfect foresight, the disutility has a much larger variance, and a much larger mean, while the median is lower when compared to the one based on statistical expectations.

4.2 Aversion to Risk or Aversion to Jail?

Can something be said about risk aversion? As long as one is willing to restrict the potential heterogeneity contained in D, the answer is yes. From the definition of D in Equation 2, I assume monthly CRRA utility functions (this implicitly assumes that robbers organize one robbery a month and consume the loot within the month), discounted at yearly rates 0.1 (low, l) and 0.5 (high, h), and with initial wealth levels equal to a fraction φ of their expected loot $W = \varphi\widehat{Y}$ that is either 0.2 (low, l) or 0.5 (high, h).

The two preference parameters that are completely free to vary are the risk aversion parameter r and the jail aversion parameter $1-\theta$, where θW measures the wealth levels upon incarceration $C(S) = (1-\theta)W$.

With these assumptions the compensating variation, or disutility of jail simplifies to

$$D = \frac{1-\delta_i^S}{1-\delta_i} W_j \left(\frac{1-\theta^{1-r}}{1-r}\right), i, j = l, h.^{48} \tag{7}$$

When incarceration is perceived as a complete loss of wealth ($\theta = 0$) all the variation has to be captured by the risk aversion parameter, which tends to be easier when r is close to one. Percentage changes in the initial wealth levels translate into percentage changes in disutility, while time dilutes the deterrent effect of S.

Since D and S are known, and δ_i, and W_i have been fixed, one can plot the distribution of r and θ that are consistent with the observed variability in D and S. The two and three dimensional histograms are shown in Figure 7. The data seem consistent with very large aversion to jail, and with risk aversion that is close to one.[49]

In summary, one has to be willing to make very strong assumptions about all the unobserved factors that determine D. Until we have more information about these factors, possibly using surveys methods, one should keep in mind that the implied heterogeneity of one preference parameter can change drastically depending on the assumptions used.

The next step is to move back to the parameter-free characterization of the disutility of jail D, and highlight the characteristics that tend to be associated with larger Ds. These tend to be related to their skills and could be used to determine the most appropriate sentence enhancements.

4.3 Disutility of Jail: Ability vs. Deterrence

Robbers with different values of freedom target different banks, and use different *modus operandi*. In order to describe such a selection, I compute the derivative of the disutility with respect to the same variables that are related to the haul and to the risk of arrest. The variables that are going to signal ability (D) might be used to set sentence enhancements that target specific types of robbers. Given that D differs across individuals, so will the derivatives of D.[50]

For the estimate of D based on statistical expectations one can analytically compute such derivatives for each robbery. The sanctioning rules (which require that judges adjust sentences proportionally to the aggravation of the robbery) suggest using the log disutility of jail instead of the level.[51] The observable characteristics of banks and bank robberies characterize the (log) disutility of jail the way one would expect, given the sanctioning rules set by the penal code. Art. 628 of the penal code sanctions masked robberies, robberies perpetrated by more than one criminal, and robberies where firearms are used more

[49]There is some experimental evidence that shows that prisoners tend to be less risk averse than students (Block and Gerety)). Estimates that are based on experimental data are typically close to 0.5, while those estimated using financial data are considerably larger (Gollier, 2004, Kocherlakota, 1996, Holt and Laury, 2002, Dohmen et al., 2010).

[50]For the sake of brevity the results that follow are based only on the exponential hazards approach. Using the Cox proportional hazards gives very similar results.

[51]Using the disutility of jail in levels gives very similar results.

strongly than "simple" robberies (*rapina semplice*). Table 6 shows the average derivative of $\log \widehat{D}(x)$ with respect to x (*modus operandi* and bank characteristics) together with its standard deviation, and the 5th and 95th percentile.

For the estimate of D based on realization one cannot analytically compute the derivatives, but one can simply regress $\log \widetilde{D}$ on x to have comparable *ceteris paribus* results. The last two columns in Table 6 show the estimated derivatives with the corresponding standard errors.

Intuitively, when using statistical expectations the averaging occurs when computing $\widehat{D}$ while when using perfect foresight the averaging occurs when regressing $\log \widetilde{D}$ on x. Despite such differences, most times the size and the significance of the derivatives are quite similar.

The use of firearms is associated with a large increase in the disutility of jail: 96 percent (with a 10 percent standard deviation) using statistical expectations and 69 percent (7 percent) using perfect foresight. Part of this increase can be explained by the sentence enhancements related to the use of firearms shown in Table 12 are coherent with the sign of the changes shown in Table 6.

Similarly, robbers using disguises have disutilities from jail that are more than 80 percent larger compared to robbers without such disguises. But these increases are considerably larger than the increase in the sentence length that one predicts based on judiciary level data (Table 12), suggesting that criminals who use firearms and mask themselves not only take longer sentences into account (thus increasing the *total* disutility) but also have a higher ability. The heterogeneity in ability is clearly visible when I derive the disutility with respect to variables that do not influence the sentence length.

Not surprisingly, robbers who operate against banks with little cash holdings are of substantially lower ability (-17 to -11 percent). Those that choose banks with less than 5 employees tend to be of higher ability (+13 to +27 percent), mainly because robberies in smaller banks are clearly less risky: bank employees need to be monitored for the duration of the robbery, therefore the greater the number of employees the riskier the robbery becomes. The number of security devices generate an ambiguous positive selection when I assume statistical expectations, while the derivative is not different from zero when I assume a perfect foresight. Robbers with larger disutilities of jail avoid banks with security guards, and banks whose security devices have more characteristics (and are presumably more advanced). However, when security devices are less visible (and presumably less predictable) the estimated disutilities are also smaller, but such difference might be driven by the very unpredictability of the reduced benefits and increased costs that is due to such technologies.

Using the standard deviation of the changes to evaluate their significance, several derivatives are not statistically different from zero. For example, the disutilities of robbers operating in a group are not different from those working on their own.[52]

4.4 Deterrence

With an estimated disutility at hand one can estimate by how much policy makers would have to increase the disutility of jail (by harshening jail sentence requirements S) to drive the number of bank robberies to zero. In terms of the estimated model, one needs to determine the level of disutility that corresponds to an optimal duration that is equal to zero, thus from Eq. 5 or 4, setting $t^* = 0$:[53]

$$\widehat{D}_{t=0} = \frac{\widehat{y}_i}{e^{\widehat{\mu}+\widehat{\gamma}'_h(x_i\widehat{\epsilon}_i)}}. \tag{8}$$

$\log \widehat{D}_{t=0} - \log \widehat{D}_{t=t^*}$ represents the percentage increase in disutility needed for robbers with an observed t^* to drive the duration to 0. Given that the only way to increase the disutility of jail is by increasing the expected jail time, deterrence is going to depend on the robbers' discount factors, as well as on the degree of time-separability of preferences, and on $C(S)$. For convenience, I assume time-separable preferences, and constant $C(S) = C$.

What matters is how an increase in (relative) jail time translates into an increase in (relative) disutility. If robbers do not discount future jail time, then a relative change in the sentence length translates fully into a relative change in the disutility $\frac{\partial \log(D)}{\partial \log(S)} = 1$. If instead robbers discount the future, the relative change in disutility is going to be smaller than the relative change in the sentence length: $\frac{\partial \log(D)}{\partial \log(S)} = \frac{-S\delta^S}{1-\delta^S} \log \delta$. The difference between these two elasticities measures how discounting attenuates deterrence. With a discount factor of 80 percent, attenuation evaluated at the average sentence (3.4 years) is equal to 70 percent. With a discount factor of 50 percent, the attenuation bias is equal to 90 percent. Table 7 shows the distribution of the changes, assuming no discounting. The 5th percentile shows that in order to drive 5 percent of the sample to a duration of zero one needs a 1 percent increase in the total disutility of jail; or , without discounting, an equivalent increase in sentence length. In order to reduce the bank robberies by

[52]Since there is no information on how robbers distribute the hauls among themselves this result in based on the assumption that robbers divide such haul in equal parts.

[53]When the Cox hazard model is used to measure the risk, one needs to take into account that the hazard at 0 might be also different.

a quarter, the penalties would have to increase by 3 percent, and to curb robberies by one-half, penalties would have to increase by 5 percent. Overall, and no matter how one models the expectations, criminal behavior is predicted to be highly responsive to changes in the sanctioning system, although discounting would attenuate this responsiveness dramatically according to the function discussed in the previous paragraph. Moreover, given the assumption of risk neutrality, robbers would be equally responsive to changes in the likelihood of arrest.

4.5 Heterogeneity in Deterrence

Table 8 shows the mean for the *modus operandi* variables and for the variables describing the banks, for values above and below the median percentage increase in disutility needed for robbers to drive the duration of bank robberies to 0. Values below the median signal high responsiveness to sanctions (the corresponding average log change in disutility is 3 percent), values above the median signal low responsiveness to sanctions (the corresponding average log change in disutility is 11 percent). Looking at the table, a clear picture emerges for both samples. Robbers with higher disutilities of jail (€296 vs. €136.36 and €865 vs. €98), who are more likely to be professional robbers, are also more responsive to increases in sentence lengths. In particular, robbers that use firearms are much more likely to belong to the high responsiveness category. Masked robbers are also considerably more likely to be highly responsive (60 versus 44 percent). This means that harshening sentencing guidelines would mostly deter those robbers that are responsible for the largest losses. The amateur robbers would most likely keep on trying to rob banks.[54]

5 Conclusions

During bank robberies both the probability of apprehension and the average haul increase over time. Assuming that robbers averse the risk of jail but not the uncertainty about the loot (possibly because such uncertainty is resolved as soon as the robbers starts collecting the loot), I show that for arbitrary utility functions, arbitrary initial wealth levels, and arbitrary preferences against jail time the trade-off depends on: i) the criminal's expected haul at time t, ii) its expected increase between t and t+1; iii) the hazard rate of arrest, and iv) the criminals' disutility of ending up in jail, which can be interpreted as the compensating variation when incarceration occurs.

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

Unique data on 5,000 Italian bank robberies–representing 57 percent of all European bank robberies–with information on the observed robbery duration for successful robberies, allow me to identify and then analyze the individual disutility of jail. The compensating variation depends on several unobserved factors (risk aversion, initial wealth, discount factors, aversion to jail) that that can be left unspecified.

The vast majority of criminals face relatively low disutilities of jail, while a few face very high ones. The shape of the distribution of the estimated D resembles the shape of an earnings distribution.

Simulating relative changes in deterrence, my results suggest that the most responsive robbers to deterrence are the more able ones, who have a higher disutility of ending up in jail because their opportunity cost of prison time is higher. The estimated level of deterrence to the severity of sanctions varies significantly depending on the assumptions made on robbers' discounting.

The most able criminals tend to rob banks using firearms and wearing a disguise. They are also more likely to target the right banks (those with higher cash holdings but fewer employees). This differential deterrence potential, coupled with considerably harsher sentences (the average prison sentence is 137 months in the US and just 40 months in Italy), is likely to explain why nowadays, unlike their Italian fellows, US bank robbers "are clearly amateurs and not bank robbery specialists." (Department of Justice, 2003). The results are robust to the inclusion of unobserved robber ability and heterogeneity in expectations for the haul and the risk. The hypothesis that robbers a risk averse is rejected by the data.

The relatively large number of bank robberies, together with evidence of possibly large deterrence effects from harsher prison terms, suggests that in Italy prison sentences might be too low. It appears that rather than the legislators, it is instead the judges who should reconsider their customs. Actual sentences are often below the minimum ones set by law. Despite well-designed sentence enhancements that penalize *modus operandi* linked to high-ability robbers, judges (with the exception of the use of firearms) tend to neglect these guidelines.

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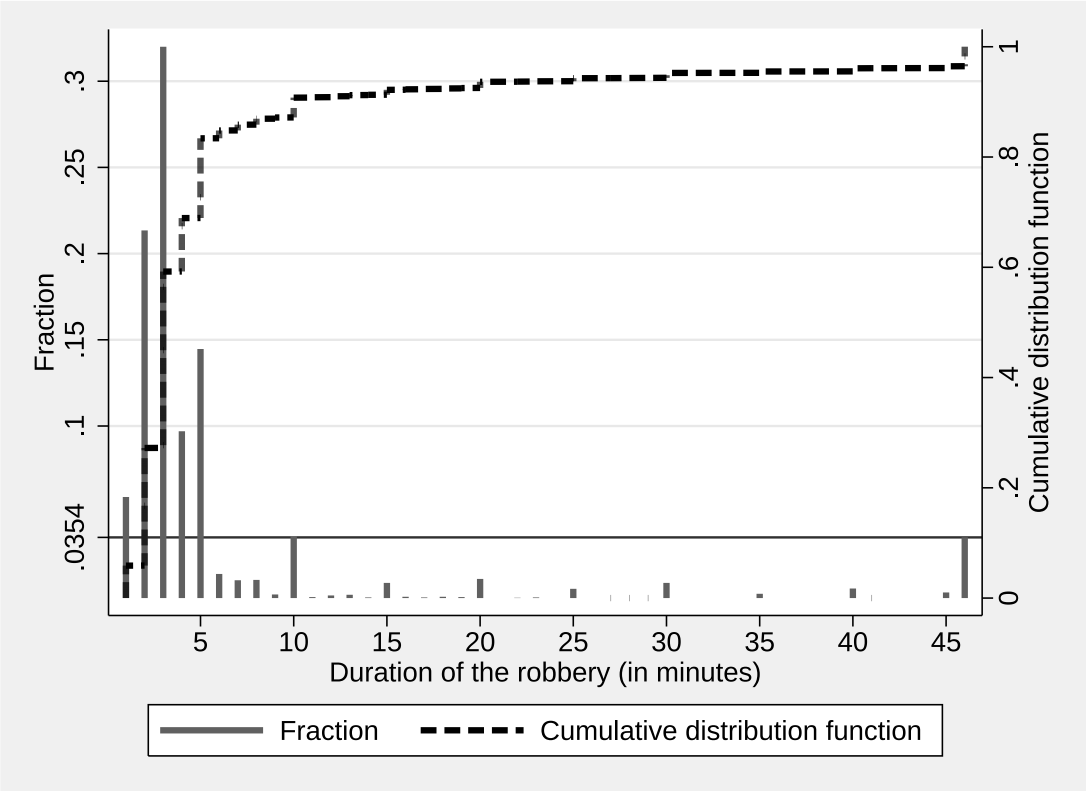


Figure 1: The Distribution of the Duration of Bank Robberies

Notes: The spikes indicate the distribution of duration (on the left axis) while the dashed line indicates its cumulative distribution (on the right axis). Minute 46 stands for all the durations that lasted more than 45 minutes.

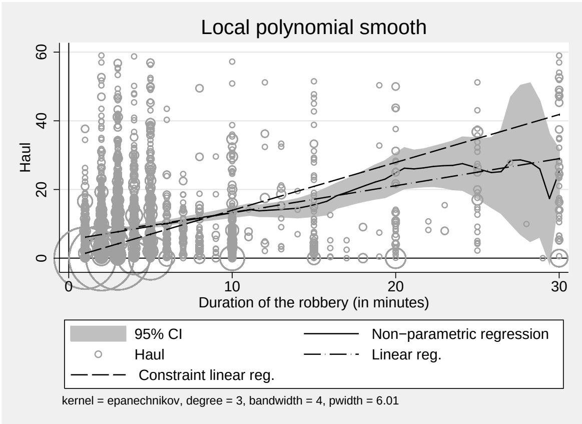


Figure 2: Haul and Time Spent Inside the Bank

Notes: The y-axes show the haul (in €1,000), the x-axes the duration of the robbery. Circles (proportional to their frequency) show the raw data and are truncated at 60,000 euro (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).

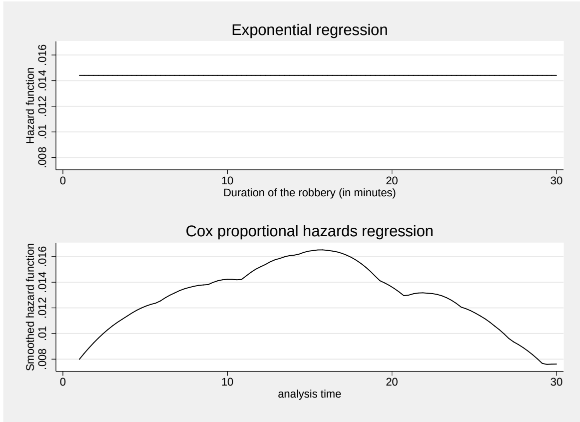
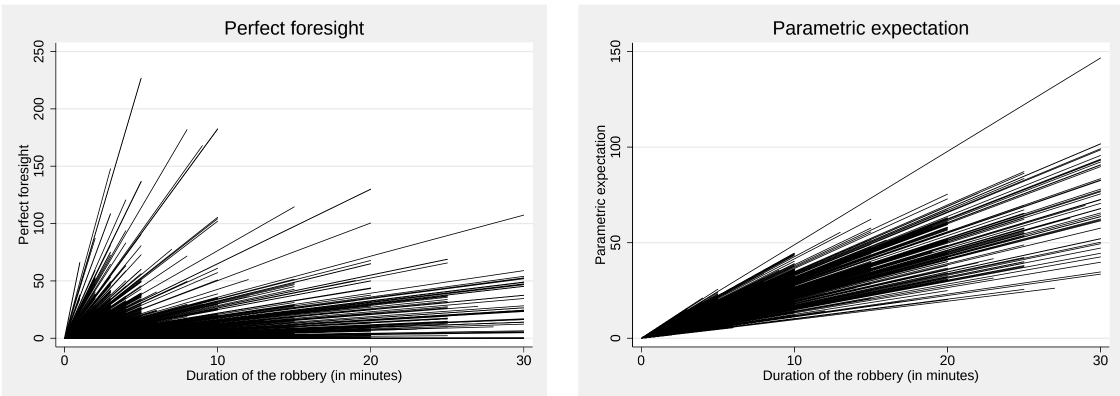


Figure 3: The Estimated Hazard Rate

Notes: The Cox proportional hazard is estimated applying an Epanechnikov kernel smoothing with optimal bandwidth on the estimated increments of the cumulative hazards.

Figure 4: Predicted Hauls and Marginal Hauls



Notes: The figure on the left shows the actual realizations (the endpoints, Y) connected with the origin (the perfect foresight hypothesis). The slope of these lines are the predicted marginal hauls, Y/t. The figure on the right shows the predicted expectations (the endpoints, $\widehat{y} \times t$), based on regression shown in Table 3, connected with the origin.

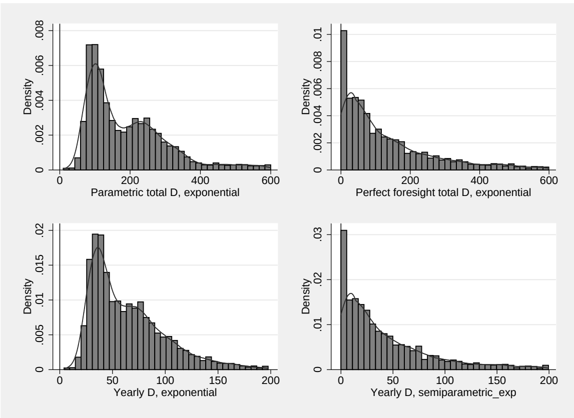


Figure 5: The Distribution of the Conditional Disutility of Jail

Notes: The left figure shows the distribution (capped at €600,000) of the total disutility of jail, the right one the corresponding yearly figures (capped at €200,000) assuming a discount factor of one.

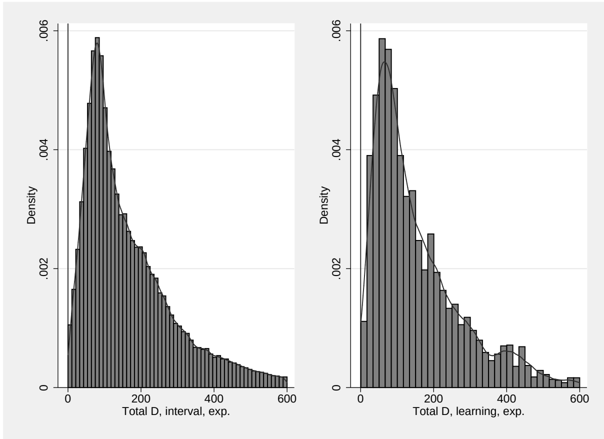


Figure 6: Densities of Disutility Intervals and of Disutility with Learning

Notes: The left figures shows the distribution of equally weighted intervals bound between the estimates of disutility based on statistical expectations and those based on perfect foresight of the total disutility of jail, the right ones show the estimate based on a learning model shown in Eq. 6. The upper (lower) figures use exponential (Cox) hazards. All values are capped at €600,000.

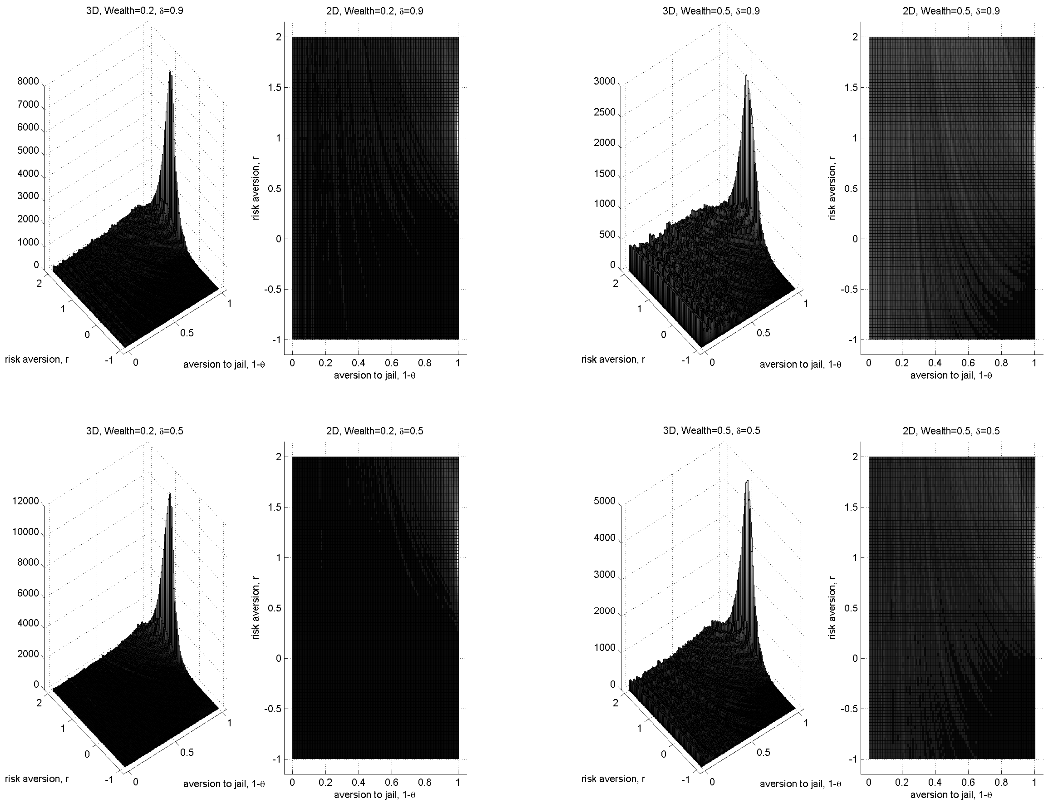


Figure 7: The Distribution of Risk Preferences

Notes: The density and CDF of the CRRA risk aversion parameter when $W = 0$, $\delta = 1$, and U(C(S)=and Each plot show the distribution of the total disutility of jail for different degrees of risk aversion (between the first and the 99th percentile). The values based on the risk version parameter $r = 2$ are divided by 10.

Table 1: "Life Table" of Bank Robberies

Time	Number surviving to time $t-1$	Arrested	Successful	Total
		between $t-1$ and t		
1	4972	24	273	297
2	4675	71	1049	1120
3	3555	99	1572	1671
4	1884	31	477	508
5	1376	53	702	755
6	621	4	71	75
7	546	5	50	55
8	491	1	55	56
9	435	0	12	12
10	423	20	169	189
11	234	0	4	4
12	230	0	9	9
13	221	2	9	11
14	210	0	3	3
15	207	7	41	48
16	159	1	4	5
17	154	1	2	3
18	151	5	0	5
19	146	0	4	4
20	142	9	49	58
22	84	0	2	2
23	82	0	3	3
25	79	0	29	29
27	50	0	1	1
28	49	0	1	1
29	48	0	1	1
30	47	3	44	47

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

Table 2: Summary statistics

Sample	Whole		duration $\leq 3min$		duration $> 3min$	
	Mean	SD	Mean	SD	Mean	SD
Arrested	6.76%	25.10%	6.28%	24.27%	7.54%	26.41%
Duration of the robbery (in minutes)	4.32	4.29	2.44	0.66	7.40	5.72
Total haul	15,996	29,749	11,559	14,959	23,269	43,408
Haul	8,690	13,609	7,025	8,736	11,419	18,757
Firearms	0.15	0.36	0.12	0.33	0.20	0.40
Two robbers	0.52	0.50	0.51	0.50	0.54	0.50
Three or more robbers	0.16	0.37	0.11	0.32	0.23	0.42
Masked robbers	0.44	0.50	0.43	0.50	0.45	0.50
Center Italy	0.21	0.41	0.20	0.40	0.22	0.41
Southern Italy	0.29	0.45	0.27	0.45	0.31	0.46
Guarded	0.08	0.27	0.07	0.26	0.09	0.29
Isolated branch	0.25	0.43	0.25	0.43	0.23	0.42
Bank with little cash	0.63	0.48	0.62	0.48	0.64	0.48
Bank with less than 5 employees	0.51	0.50	0.50	0.50	0.53	0.50
Number of Security Devices (S.D.)	5.62	1.18	5.62	1.16	5.63	1.21
Average Number of Characteristics per S.D.	1.26	0.38	1.27	0.39	1.24	0.35
% of invisible devices	0.68	0.16	0.68	0.16	0.67	0.16
N.obs.	4,972		3,088		1,884	

Notes: This table shows the summary statistics for the sample of bank robberies that last less than 30 minutes. The last four columns split the sample depending on whether the duration is above or below the median (3 minutes).

Table 3: Linear Regressions of the Per-Capita Haul

	(1)	(2)
	Haul per minute	
Firearms	714.09***	703.82***
	(184.636)	(185.992)
Two robbers	-1,216.53***	-1,292.00***
	(133.755)	(136.426)
Three or more robbers	-1,546.50***	-1,625.06***
	(172.182)	(172.242)
Masked robbers	572.70***	500.93***
	(114.951)	(113.306)
Center Italy		541.57***
		(167.003)
Southern Italy		330.35***
		(127.072)
Isolated branch		-150.29
		(115.307)
Bank with little cash		-230.64*
		(121.858)
Bank with less than 5 employees		-219.76*
		(113.898)
Number of Security Devices		-69.40*
		(40.115)
Average Number of Characteristics per Security Device		-406.83***
		(136.339)
% of invisible devices		-425.84
		(299.000)
Guarded		-359.33**
		(182.144)
Constant	3,111.55***	4,502.27***
	(111.806)	(431.922)
Observations	4,972	4,972
R-squared	0.034	0.041

Notes: The haul per minute is modeled as a linear function of the *modus operandi*. Robust standard errors in parentheses: : *** p<0.01, ** p<0.05, * p<0.1

Table 4: Hazard Models of Arrest

	(1)	(2)	(3)	(4)
	Exponential		Cox Proportional	
Parametric residual marginal haul		-0.06**		-0.04
		(0.029)		(0.027)
Firearms	-0.63***	-0.65***	-0.67***	-0.67***
	(0.178)	(0.178)	(0.180)	(0.180)
Two robbers	-0.57***	-0.55***	-0.64***	-0.62***
	(0.116)	(0.116)	(0.119)	(0.118)
Three or more robbers	-0.76***	-0.73***	-0.87***	-0.84***
	(0.168)	(0.168)	(0.173)	(0.172)
Masked robbers	-0.59***	-0.59***	-0.57***	-0.57***
	(0.120)	(0.120)	(0.122)	(0.121)
Center Italy	-0.10	-0.11	-0.11	-0.12
	(0.148)	(0.149)	(0.150)	(0.150)
Southern Italy	-0.04	-0.05	-0.07	-0.07
	(0.129)	(0.128)	(0.130)	(0.129)
Isolated branch	-0.13	-0.12	-0.12	-0.12
	(0.134)	(0.134)	(0.135)	(0.136)
Bank with little cash	0.07	0.07	0.06	0.06
	(0.109)	(0.109)	(0.110)	(0.110)
Bank with less than 5 employees	-0.32***	-0.33***	-0.35***	-0.36***
	(0.109)	(0.110)	(0.111)	(0.111)
Number of Security Devices	-0.09**	-0.09**	-0.08*	-0.08*
	(0.044)	(0.043)	(0.044)	(0.044)
Average Number of Characteristics per Security Device	0.08	0.07	0.13	0.12
	(0.138)	(0.139)	(0.141)	(0.142)
Guarded	0.13	0.14	0.17	0.17
	(0.214)	(0.214)	(0.217)	(0.216)
N.obs.	4,972	4,972	4,972	4,972

Notes: This table shows the estimated coefficients of an exponential (columns 1-2) and a Cox proportional (columns 3-4) hazard model of arrest. The parametric residual of the marginal haul is the predicted error term from Column 2, Table 3. Robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Conditional Heterogeneity in $\widehat{D}$ (times €1,000s)

	% Negative	Mean	St. Dev.	C. Var.	P10	P25	P50	P75	P90
				Total disutility					
Statistical expectations, exponential	0.000	216.20	330.19	1.53	75.37	95.05	155.53	250.39	398.21
Perfect foresight, exponential	0.000	446.85	4585.91	10.26	4.74	35.21	97.59	234.83	500.39
Learning, exponential	0.000	289.21	1741.41	6.02	37.25	64.01	118.18	226.53	407.43
				Yearly disutility					
Statistical expectations	0.000	65.05	104.65	1.61	26.89	33.93	51.61	77.94	107.89
Perfect foresight	0.000	136.77	1582.09	11.57	1.56	11.95	31.67	73.40	159.73
Learning	0.000	84.97	448.18	5.27	12.74	21.51	39.34	71.72	126.37

Notes: This table shows the mean, the standard deviation, the compensating variation, and the 10th, 25th, 50th, 75th, and 90th percentile of the disutility of jail, based on the exponential hazard. The yearly figures are estimated dividing the yearly figures by the predicted sentence length based on the regression shown in Column 3 of Table 12.

Table 6: log-Disutility of Jail Changes

	Parametric estimate				Perfect foresight	
	Average	SE	P5	P95	Average	SE
Firearms	0.96	0.10	0.83	1.12	0.69	0.07
Two robbers	0.01	0.38	-1.64	0.24	-0.05	0.06
Three or more robbers	-0.29	0.75	-3.28	0.31	-0.10	0.08
Masked robbers	0.84	0.08	0.73	0.96	0.81	0.05
Center Italy	0.33	0.06	0.23	0.44	0.23	0.07
Southern Italy	0.19	0.05	0.13	0.27	0.04	0.06
Isolated branch	0.07	0.03	0.00	0.10	0.19	0.06
Bank with little cash	-0.17	0.04	-0.27	-0.13	-0.11	0.05
Bank with less than 5 employees	0.27	0.05	0.18	0.33	0.13	0.05
Number of Security Devices	0.07	0.03	0.05	0.09	-0.02	0.02
Average Number of Characteristics	-0.23	0.04	-0.35	-0.17	-0.18	0.07
% of invisible devices	-0.17	0.06	-0.35	-0.11	-0.71	0.17
Guarded	-0.31	0.09	-0.52	-0.24	-0.25	0.10

Notes: The left columns shows the analytical log-changes in the disutility of jail that correspond to a unitary change in the use of firearms, etc, together with the standard deviation, the 5th and the 95th percentile based on the parametric model. The right columns show the corresponding estimates from a regression of $\widetilde{D}$ (based on perfect foresight).

Table 7: Percentage Change in $\log D$ that Corresponds to $t^* = 0$

	Mean	St. Dev.	P5	P25	P50	P75	P95
Statistical expectations	0.07	0.10	0.01	0.03	0.05	0.08	0.19
Perfect foresight	0.07	0.09	0.01	0.03	0.05	0.08	0.19

Notes: This table shows the mean, the standard deviation, and the 5th, 25th, 50th, 75th, and 95th percentile of $\Delta \log \widehat{D}$ that is needed to drive the optimal duration of the bank robbery to 0, based on the exponential hazard.

Table 8: High and Low Responsiveness

	Average characteristic			
	Statistical expectations		Perfect foresight	
Responsiveness	*high*	*low*	*high*	*low*
Change in $log\widehat{D}$	0.03	0.11	0.03	0.11
Disutility	296.05	136.36	865.46	98.07
Firearms	0.22	0.09	0.21	0.10
Two robbers	0.61	0.44	0.61	0.45
Three or more robbers	0.17	0.14	0.17	0.14
Masked robbers	0.63	0.26	0.63	0.26
Center Italy	0.26	0.16	0.27	0.15
Southern Italy	0.28	0.30	0.27	0.29
Isolated branch	0.29	0.21	0.29	0.21
Bank with little cash	0.64	0.62	0.63	0.62
Bank with less than 5 employees	0.56	0.47	0.57	0.47
Number of Security Devices	5.71	5.55	5.70	5.55
Average Number of Characteristics	1.25	1.27	1.25	1.26
% of invisible devices	0.68	0.68	0.67	0.68
Guarded	0.08	0.08	0.08	0.07

Notes: This table shows the average X's according to whether the $\Delta \log \widehat{D}$ needed to drive the optimal duration of the bank robbery to 0 is above or below the median. A lower change corresponds to a higher *responsiveness*.

A Online Appendix

A.1 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 percent 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 reveal that Italy is followed by Canada and Germany, which have around 800 robberies per year, and by Spain with 500 (Table 9). 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' fear 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. And the trend over time is not wholly encouraging. Figure 8 shows the average haul (right axis) and the number of bank robberies (left axis) between 1990 and 2003. While the average haul went down, the number of bank robberies went from around 1,500 in the early 90s to almost double that number 10 years later.

Perceived costs of robbing banks depend on the probability of apprehension and on the expected sanctions. More than 90 percent of Italian bank robberies end up without an arrest, while in the US 33 percent of bank robbers are already arrested on the same day they commit the robbery. Moreover, US federal guidelines impose sentences of *at least* 20 years (plus 5 years when a weapon is used), while in Italy the sentence length ranges 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 group, violence is used to incapacitate a victim, or the robber belongs to an organized crime association.

The expected costs of robbing a bank are, therefore, considerably lower in Italy than in the US. What about the expected benefits? Robbing a bank seems to pay in Italy. The average haul is almost €20,000 (in the US it is approximately €6,000). This leads to a direct cost for society of more than €57 million a year.[55] But the indirect cost is even larger. A survey of 21,000 retail bank branches representing 65 percent of all Italian branches shows that in 2006 banks spent an average of €10,700 per branch to prevent bank

[55] While these costs might be regarded as transfers from victims to perpetrators, costs that are not transferable are an order of magnitude larger.

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 euro (European Commission, 2007). Moreover, Miller-Burke et al. (1999) show that in the U.S. 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 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 reason for this is certainly the lack of data.

A.2 The Expected Sentence Length

Table 11 shows the summary statistics for the sample of 323 bank robberies attributed to 96 different bank robbers who were sentenced to jail in the Piedmont region, located in Northern Italy, between 2005 and 2007. This means that in the sample each robber has been convicted based on an average of 3.4 bank robberies. The bank robbers are on average 35 years old, most are Italian (92 percent), and despite the convictions coming from a Northern region, 35 percent were born in the south of Italy. 67 percent of the robbers are recidivists and 34 percent accept a plea bargain. The other variables vary by robbery. In 22.5 percent of the cases robbers use firearms (versus 13.7 percent from the Italian Banking Association data), in 57.2 percent they wear a mask (versus 42.7 percent) and in 68.9 percent they work in teams (versus 66.3 percent). 4 percent of the time the robber uses hostages. The average total haul is €12,374, slightly lower than the total haul based on the banking data. While the *modus operandi* of robbers that were sentenced in Piedmont are on average slightly different than in the country-wide 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. Unless, judges in Piedmont make systematically different judgments.

The average sentence length is 3.4 years in prison. Data on sentence durations allows me to model the log-sentence length based on the same *modus operandi* variables observed for the bank robberies and to impute the variation in the log-Disutility of jail, D, that is driven by the variation in the sentence length, S, $\log(D) = \log(d) + \log(S)$. Thus

$\log(D) - \log(S) = \log(d)$ represents the log-Disutility for each year in jail.[56]

In order to determine the way the *modus operandi* shapes the expected sentence length S, I estimate the log-sentence length on whether the robber used firearms, was masked, or worked in a group. Estimates are shown in Table 12. Based on Column 1, using a firearm increases the sentence by approximately 39 percent (by less once I control for recidivism, hostages, plead bargain, year, total number of robberies committed, total haul). Wearing a mask and working in groups has a smaller effect on the sentence. Working in groups increases the sentence length by 20 percent, and being disguised increases it by less than 10 percent but without being statistically different from zero. Only the use of firearms leads to strong and significant sentence enhancements. This likely explains why so many robbers choose to work in groups and to wear a mask, while so few use a firearm.

Table 9: Number of Bank Robberies Across the World

	Total Robberies	R. per Branch (in %)		Total Robberies	R. per Branch
Andorra	0	0	Japan	133.29	0.98
Australia	119	2.54	Liechtenstein	0	0
Belgium	117.43	1.37	Lithuania	12.29	1.79
Bulgaria	1	0.32	Luxembourg	2.14	0.71
Canada	827.71	14.1	Malta	0.71	0.7
Croatia	27.43	2.45	Monaco	0	0
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
Germany	837.71	1.96	Spain	523.43	1.36
Greece	143.57	3.68	Sweden	38.86	2
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.

[56] Notice that I used a discount factor $\delta = 1$, otherwise $log(D) = \log(d) + \log(\frac{1-\delta^S}{1-\delta})$.

Table 10: Linear Regressions of the Per-Capita Haul Excluding the Robberies With Zero Haul

	(1)	(2)
	Haul per minute	
Firearms	805.77***	814.68***
	(199.73)	(201.02)
Two robbers	-1,395.52***	-1,497.41***
	(143.41)	(146.72)
Three or more robbers	-1,714.42***	-1,857.14***
	(185.26)	(185.28)
Masked robbers	639.96***	558.87***
	(122.30)	(120.44)
Center Italy		584.74***
		(176.23)
South Italy		469.12***
		(138.07)
Isolated branch		-218.09*
		(122.17)
Bank with little cash		-157.21
		(129.18)
Bank with less than 5 employees		-302.71**
		(120.55)
Number of Security Devices		-72.16*
		(43.11)
Average Number of Characteristics per Security Device		-340.50**
		(146.98)
% of invisible devices		-156.26
		(319.17)
Guarded		-224.14
		(199.88)
Constant	3,437.82***	4,557.31***
	(120.47)	(462.72)
Observations	4549	4549
R-squared	0.042	0.050

Notes: The haul per minute is modeled as a linear function of the *modus operandi*. Robust standard errors in parentheses: : *** p<0.01, ** p<0.05, * p<0.1

Table 11: Summary Statistics from Trials Related to Bank Robberies

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
	Characteristics of bank robbers				
Age	35.691	10.194	18	65	94
Foreigner	0.083	0.278	0	1	96
Southern	0.344	0.477	0	1	96
Number of robberies	3.365	3.369	1	15	96
Recidivist	0.667	0.474	0	1	96
Plea bargain	0.344	0.477	0	1	96
Total sentence	3.452	1.647	1.333	12.667	94
	Characteristics of robberies				
Firearms	0.22	0.415	0	1	323
Masked	0.570	0.496	0	1	323
Group robbery	0.687	0.464	0	1	323
Hostages	0.04	0.197	0	1	323
Total haul	12.417	21.667	0	145	323
Year	2004.898	1.474	1993	2007	322

Notes: These data are based on trials against 95 bank robbers, involved in a total of 323 bank robberies organized between 1997 and 2007, that were held in the judicial district of Piedmont.

Table 12: 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 95 bank robbers, involved in a total of 323 bank robberies organized between 1997 and 2007, that were held in the judicial district of Piedmont. Robust standard errors in parentheses: : *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 13: Conditional Heterogeneity in $\widehat{D}$ (times €1,000s)

	% Negative	Mean	St. Dev.	C. Var.	P10	P25	P50	P75	P90
				Total disutility					
Statistical expectations, exponential	0.000	216.20	330.19	1.53	75.37	95.05	155.53	250.39	398.21
Statistical expectations, Cox	0.016	205.57	426.23	2.07	35.96	61.56	112.94	222.50	385.20
Perfect foresight, exponential	0.000	446.85	4585.91	10.26	4.74	35.21	97.59	234.83	500.39
Perfect foresight, Cox	0.014	423.50	4846.16	11.44	1.04	18.90	68.71	191.02	488.10
Learning, exponential	0.000	289.21	1741.41	6.02	37.25	64.01	118.18	226.53	407.43
Learning, Cox	0.016	228.64	732.58	3.20	17.54	41.16	91.97	213.68	438.12
				Yearly disutility					
Statistical expectations, exponential	0.000	65.05	104.65	1.61	26.89	33.93	51.61	77.94	107.89
Statistical expectations, Cox	0.016	62.48	122.72	1.96	12.55	21.23	37.42	67.83	115.86
Perfect foresight, exponential	0.000	136.77	1582.09	11.57	1.56	11.95	31.67	73.40	159.73
Perfect foresight, Cox	0.014	132.00	1676.14	12.70	0.36	6.42	23.12	61.45	153.74
Learning, exponential	0.000	84.97	448.18	5.27	12.74	21.51	39.34	71.72	126.37
Learning, Cox	0.016	68.79	200.24	2.91	5.84	14.08	30.12	66.92	137.76

Notes: This table shows the mean, the standard deviation, the compensating variation, and the 10th, 25th, 50th, 75th, and 90th percentile of the disutility of jail using the exponential and Cox proportional hazard rates. The yearly figures are estimated dividing the yearly figures by the predicted sentence length based on the regression shown in Column 3 of Table 12.

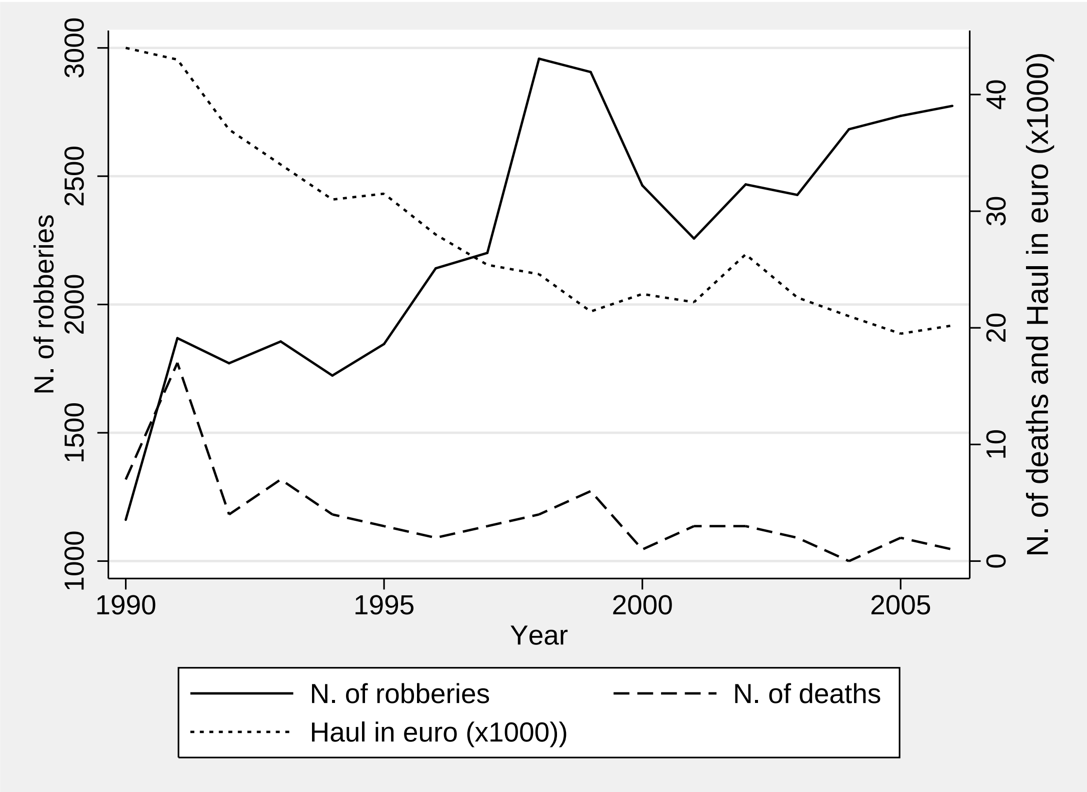


Figure 8: Number of Italian Bank Robberies, Average haul, and of the Number of Casualties

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

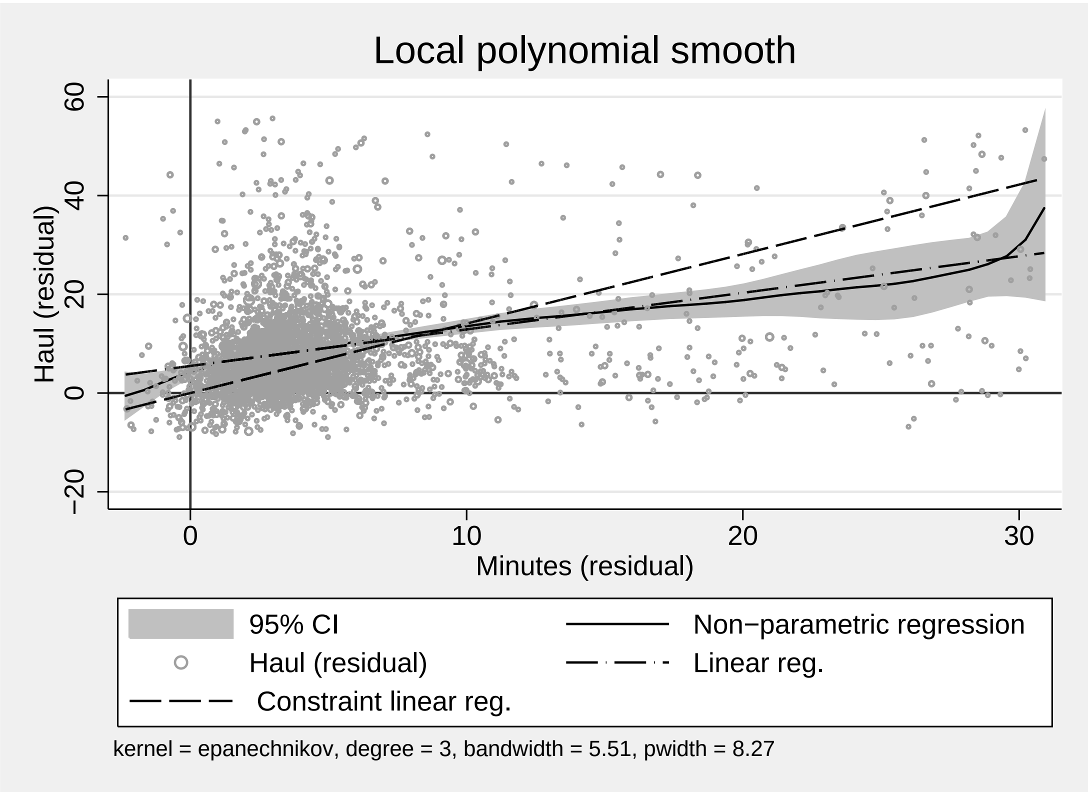


Figure 9: Haul and Time Spent Inside the Bank

Notes: The y-axes show the residual haul (plus its mean), the x-axes the residual duration of the robbery (plus its mean), where the residual are based on a projection on the following variables *Firearms, Two robbers, Three or more robbers, Masked robbers, Center Italy, Southern Italy, Guarded, Isolated branch, Bank with little cash, Bank with less than 5 employees, Number of Security Devices, Average Number of Characteristics, and % of invisible devices.* The non-parametric fit is based on a locally polynomial regression of degree 3 with asymptotically optimal constant bandwidth (Fan and Gijbels, 1996).

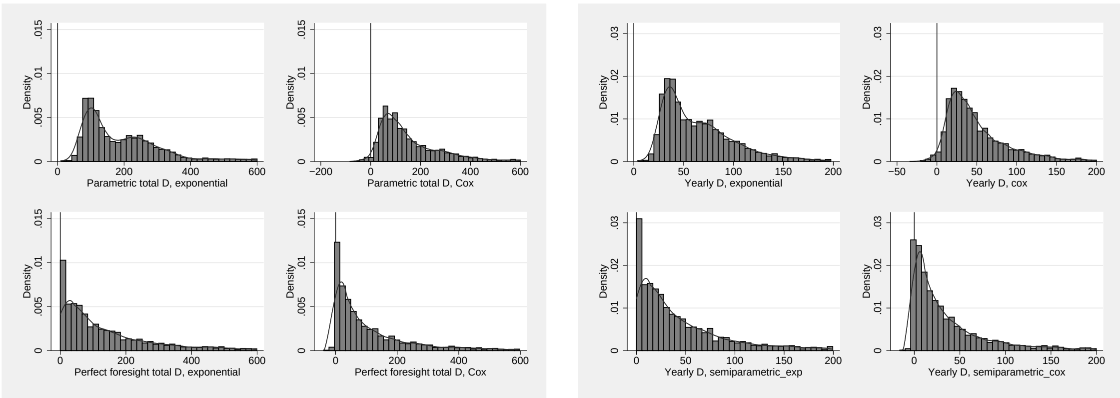


Figure 10: The Distribution of the Conditional Disutility of Jail

Notes: The left figure shows the distribution (capped at €600,000) of the total disutility of jail, the right one the corresponding yearly figures (capped at €200,000) assuming a discount factor of one.

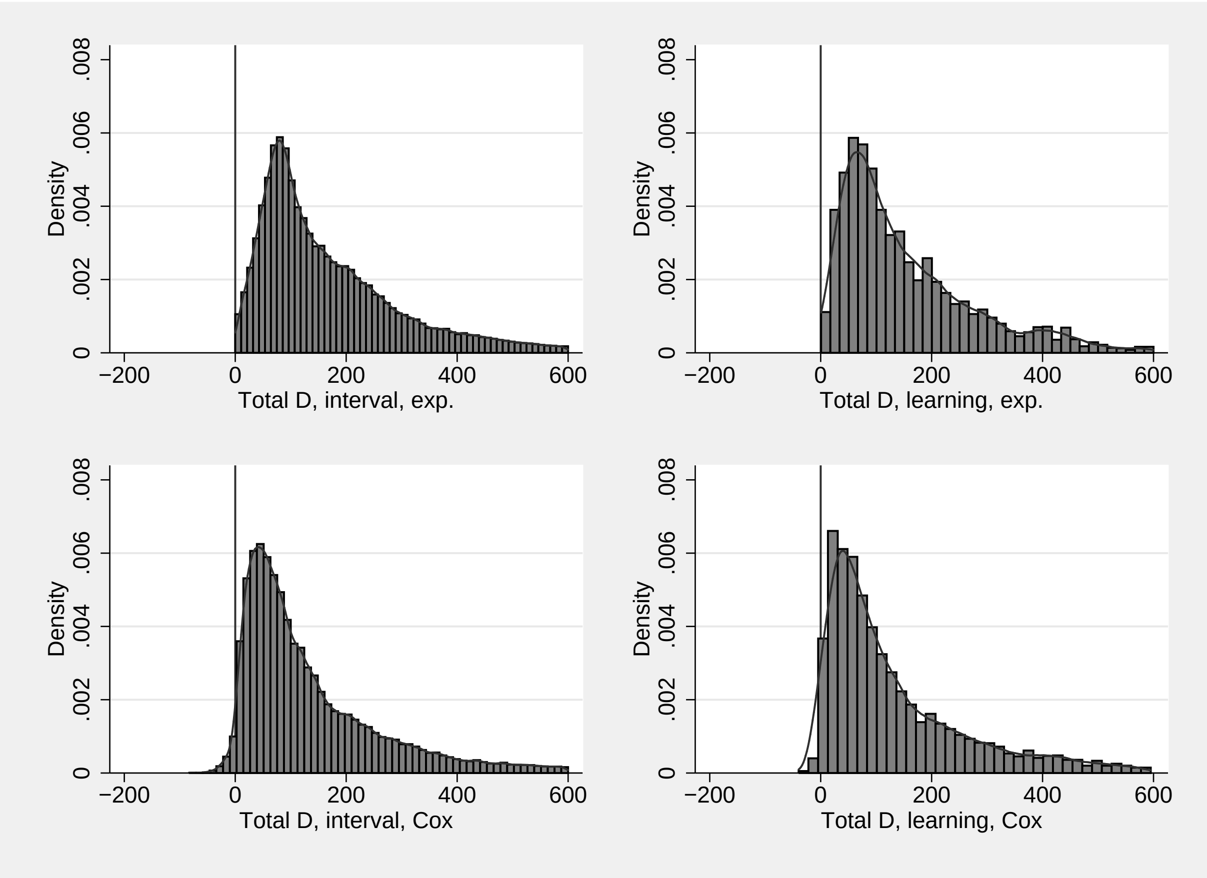


Figure 11: Densities of Disutility Intervals and of Disutility with Learning

Notes: The left figures shows the distribution of equally weighted intervals bound between the estimates of disutility based on statistical expectations and those based on perfect foresight of the total disutility of jail, the right ones show the estimate based on a learning model shown in Eq. 6. The upper (lower) figures use exponential (Cox) hazards. All values are capped at €600,000.