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

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Abstract

This paper uses unique data on the benefits of individual crimes, in particular, 5,000 Italian bank robberies – representing 57 percent of all European bank robberies - to identify the distribution of criminals' perceived disutility of jail or value of freedom. Bank robbers behave according to an instantaneous version of Becker's model of crime: during bank robberies both the probability of apprehension and the average haul increase over time. At the margin this 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. The optimal duration t^* in successful robberies allows me to identify the individual disutility of ending up in jail or value of freedom. The distribution of the disutility of jail is positively skewed and resembles a typical earnings distribution. Ability among criminals appears to be distributed like ability among workers since both earnings and the disutility of jail – an opportunity cost that is larger for more able criminals – arise from an underlying distribution of ability. Moreover, the relationship between the modus operandi of bank robberies and the derived disutility of jail time is consistent with the existence of general deterrence. Sentence enhancements appear to be correctly targeting the most able bank robbers. Finally, more able bank robbers are considerably more responsive to deterrence than less able ones.

Keywords: Crime, Deterrence, Sentence Enhancements, Bank Robberies, Value of Freedom, Disutility of Jail JEL classification codes: K40, K42, H11

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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." (Crais, 2007)

1 Introduction

According to the Uniform Crime Statistics each year in the U.S. there are around 10,000 bank robberies, representing more than 10 percent of all commercial robberies, with an average loss 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. In order to fight these crimes it is of uttermost importance to understand criminal behavior. This paper sheds light on criminal strategies used during robberies. Based on unique data of individual Italian bank robberies organized between between 2005 and 2007 this paper identifies the criminals' *individual* disutility of jail and their responsiveness to changes in sentencing. Given that sentence length is used by the criminal justice system to modify the criminals' disutility of jail, knowing the disutility's distribution allows one to assess the individual response to sanctions, going beyond the average response. Moreover, the disutility is needed 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, 2008).

The identification is based on a simple model of the crime. Rational models of crime predict that criminals commit an additional crime whenever the expected marginal utility that they derive from the crime is larger than the expected marginal sanction. Richard Freeman in a chapter titled "The Economics of Crime" of his Labor Economics Handbook formalizes a discrete version of this model. He defines W_c to be the gain from successful crime, p the probability of being apprehended, S the extent of punishment, and W the earnings from legitimate work. The criminal chooses to commit a crime in a given time period rather than do legitimate work when:

$$(1-p)U(W_c) - pU(S) > U(W) . (1)$$

Even though the model is simple and intuitive it has been difficult to estimate. Data available to researchers is typically aggregated across space and time, which makes it difficult to measure legal and illegal earnings (Vicusi, 1986b). Measurement errors have plagued the measurement of W_c and simultaneity issues (policy makers increase police enforcement and the severity of sanctions when crime levels are high) have made the estimation of the deterrence effect of the probability of apprehension p difficult. The disutility of apprehension U(S), which can also be interpreted as the opportunity cost of jail, is not observed and makes the estimation still more challenging. Moreover, extensions of the model that would increase its realism–such as additional allocations of time, the effect of crime or apprehension in one period on future legitimate and criminal earnings, the risk that a criminal is victimized by other criminals, the degree of social stigma associated with crime, and perhaps the possibility that crime and legal work are not exclusionary acts–complicate the estimation even further.

Some studies have estimated Eq. 1 using individual level data on perceived deterrence but such data is usually based on prison surveys (Polich et al., 1980) or on other selfreported crime data (Grogger, 1998, Glaeser and Sacerdote, 1999).¹ In both surveys and self-reports crime activities might be subject to untruthful reporting or at least to underreporting (Vicusi, 1986a). Kessler and Levitt (1999) use the introduction of sentence enhancement while Helland and Tabarrok (2007) use a quasi-randomization of sentence enhancements to isolate deterrence and find strong evidence of it. Lee and McCrary (2005), instead, find very little evidence of deterrence among juvenile criminals who move

¹Nagin (1998) and Cameron (1988) survey the hundreds of papers written on deterrence.

to the adult sanctioning system: their criminal behavior changes very little upon turning 18. Drago et al. (2009) use an Italian quasi-experimental setting and find evidence of deterrence. All these studies estimate *average* deterrence effects. This paper goes a step further, identifying individual responsiveness to sanctions.

There is only one other paper, Abrams and Rohlfs (2010), that estimates the disutility of jail but the average one. Based on data on posting bails the authors' estimate is around \$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 just estimating the average disutility of jail, backing out, under some parametric assumptions, its whole distribution. The identification is based on an instantaneous version of the tradeoff modeled below in Eq. 1. The model's first order conditions are used to solve for the only unknown part that determines the *modus operandi* of bank robberies, i.e. the disutility of jail time. 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 driving Ashenfelter and Greenstone (2004).

Results show that the distribution of disutility of jail time is positively skewed and resembles the earnings distribution. This heterogeneity in the criminals' "fear of jail" might depend on how much they discount the future (DiIulio, 1996), but is also likely to depend on their opportunity cost of spending jail time. Changes in the disutility of jail are predicted to lead to significant changes in criminal behavior, more among high ability criminals than among low ability ones. Harshening the rather mild sanctions (the average sentence for a bank robbery is 3.3 years in Italy and 11.4 years in the US) would thus be one way to reduce Italy's dramatic number of bank robberies, especially the more profitable ones.

2 Italian Bank Robberies and the Data

Fifty-seven percent of Europe's bank robberies happen in Italy (Kington, 2007). Italy has approximately 3,000 bank robberies every year. 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 1). The U.S., which is not part of the Federation, has more than 5 times the population of Italy but just 3 times as many bank robberies (Weisel, 2007). Only when these numbers are expressed in per branch terms does Canada have more robberies than Italy (14 vs. 8 percent). Denmark also has almost as many bank robberies as Italy. Table 2 shows that what Canada, Denmark, and Italy have in common is a very high probability of success of bank robberies, while Canadian robberies have on average a very low haul. Several other factors are likely to drive these differences across countries.

Apart from low probabilities of apprehension and large cash holdings, mild sentencing, and the banks' fear that more stringent security devices—for example separating windows between tellers and clients, lowering cash holdings, etc— would lead to a loss of clients are probably the main drivers of Italy's high number of bank robberies. And the trend over time is not wholly encouraging. Figure 1 shows the average haul (right axis) and the number of bank robberies (left axis) between 1990 and 2003. While the average haul has been going down, the number of bank robberies went from around 1,500 in the early 90s to almost double that number 10 years later. Fortunately the number of deaths involved has plummeted after the 1991 peak of 17 deaths and is close to zero now.

Perceived costs of robbing banks depend on the probability of apprehension and on the expected sanctions. More than 90 percent of Italian bank robberies are successful and an even larger fraction end up without an arrest, while in the U.S. 33 percent of bank robbers are 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 years to 20 years only when at least one of the following conditions is satisfied (art. 628 of the penal code): a weapon is used, the robber is masked or he is not alone, violence is used to incapacitate a victim, the robber belongs to an organized crime association.²

The expected costs of robbing a bank is, therefore, considerably lower in the Italy than in US. What about the expected benefits? Robbing a bank seems to pay. The average haul is 20,000 euro (in the US it is approximately 6,000 euro). This leads to a direct cost for society that is more than 57 million euro each year. 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 euro per branch to prevent bank robberies (a total of more than 300 million euro (OSSIF, 2006)). Each branch spent an additional 4,900 euro to prevent thefts and 6,300 euro to protect financial couriers. The total amount spent by banks in 2006 to prevent thefts and robberies was more than 700 million euro. This might in part explain why Italian banks charge on average the largest account management fees in Europe: 90 euro 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 to the best of my knowledge almost no

²The exact wording of art. 628, Rapina is: Chiunque, per procurare a se' o ad altri un ingiusto profitto (*unjust profit*), mediante violenza (*violence*) alla persona o minaccia, s'impossessa della cosa mobile altrui, sottraendola a chi la detiene, e' punito con la reclusione da tre a dieci anni (*three to ten years*) e con la multa da lire un milione a quattro milioni. Alla stessa pena soggiace chi adopera violenza o minaccia immediatamente dopo la sottrazione per assicurare a se' o ad altri il possesso della cosa sottratta, o per procurare a se' o ad altri l'impunita'. La pena e' della reclusione da quattro anni e sei mesi a venti anni (*four years and 6 months to twenty years*) e della multa da lire due milioni a lire sei milioni: 1) se la violenza o minaccia e' commessa con armi (*weapons*), o da persona travisata (*masked*), o da piu' persone riunite (*in groups*); 2) se la violenza consiste nel porre taluno in stato d'incapacita' di volere o di agire (*violence is used to incapacitate a victim*); 3) se la violenza o minaccia e' posta in essere da persona che fa parte dell'associazione di cui all'articolo 416 bis (1) (*organized crime*).

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. Several studies describe in great detail robberies (Cook, 2009, 1990, 1987, 1986, 1985) and bank robberies in particular (Federal Bureau of Investigation, 2007, Weisel, 2007, Baumer and Carrington, 1986), but only one study–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 depends on past robberies, which might explain why the author finds no significant effects of the presence of security devices on robberies.

I have been granted access to a unique data set: the universe of single bank robberies perpetrated in Italy between 2005 and 2007. The data are divided into 2 parts: robberylevel data and branch-level data. 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 median duration of bank robberies is three minutes. The whole distribution of the durations separated into successful and unsuccessful robberies is shown in Table 3. Sixty durations were smaller than one minute and have been rounded to one minute. The distributions is truncated at 30 minutes, which excludes 5 percent of robberies. The distribution shows that after the 9th minute heaping might be an issue. Reporting 10, 15, 20, 25, 30 minute robberies is considerably more likely than reporting numbers that are not multiple of 5. Below 9 minutes only 5 minutes seems to be a little over-represented. Since I will be using the exact duration of bank robberies to minimize measurement error I truncate the distribution at nine minutes. This truncation excludes 861 observations out of 6,446, so a little more than 10 percent of the robberies.³ Later I will also address how measurement error influences my estimation.

The summary statistics in Table 4 show that between 2005 and 2007 only 6.33 percent

 $^{^{3}}$ As a robustness check I've used the whole sample with interval-censoring to solve the heaping problem, and results are very similar. The results are available upon request.

of bank robbers were arrested after robberies that lasted less than 9 minutes.⁴ The typical robbery lasts around 3.2 minutes and leads to a haul of 14,000 euro. Given that more than half of all bank robberies involve more than just one criminal the average haul per criminal is smaller or equal to approximately 8,000 euros. Only 14 percent of bank robberies involve firearms, as judges sanction their use with increased punishments. Around 50 percent of all bank robbers mask their face when robbing a bank. 21 percent of bank robberies happen in the Center of Italy, 28 percent in the South and the rest in the North.⁵ When compared to the distribution in the population of branches, bank robbers are more likely to choose banks that have on average smaller amounts of cash and banks that are located in isolation.

The data set is rich with information about the security devices installed in the bank. I know their type and their characteristics. 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 banks have a special entrance to the bank but the characteristics differ widely. Some have metal detectors, others have a double door where people can be trapped, others have a biometric sensor, etc., while other entrances might display all 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. The main reason for this is that 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 33 percent are clearly visible (like metal detectors, vault's time-locks, and protected teller's post). Since visible and invisible devices might have a different impact on the

⁴Fifty-nine percent of these arrests happen during the bank robbery, while the rest happens afterwards. All the results are qualitatively similar when I exclude the robberies where the arrests do not happen immediately.

⁵The following central regions separate the southern regions from the northern ones: Lazio, Marche, Toscana, Molise, and Umbria.

robbery I will control for the fraction of invisible devices. The last 4 columns of Table 4 allow a comparison between the summary statistics of robberies that last more or less than 3 minutes. The average duration of robberies is 2.44 minutes for those that last less than 3 minutes and 4.93 minutes for those the last more than 3 minutes. This difference translates into slightly larger probabilities of arrest 6.28 vs. 6.43 percent, but considerably larger hauls, 11,559 versus 18,469 euro. These differences can in part be explained by differences in the *modus operandi*. Longer robberies are more likely to be operated by teams (75 versus 62 percent), and in longer operations robbers are more likely to be using a firearm (16 versus 12 percent). 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 we model the bank robbers' decision about the duration of the bank robbery. The other observable characteristics of branches show only minor differences based on the duration of the robberies.

3 A Continuous Time Version of Becker's Model of Crime

Later I will show that bank robbers face an obvious 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. In this section I model this trade-off in order to identify the criminal's disutility of jail. Conditional on having chosen to rob a bank the criminal's expected utility V(t, x, z)is a function of the duration of the bank robbery, the characteristics of the bank z, and the bank robbers' modus operandi x:

$$V(t, x, z) = [1 - P(T < t | x, z)]E(Y | d = 0, t, x, z) - P(T < t | x, z)D$$
$$= [1 - F(t | x, z)]E(Y | d = 0, t, x, z) - F(t | x, z)D,$$
(2)

where P(T < t|x, z) = F(t|x, z) represents the probability of apprehension before time t, E(Y|d = 0, t, x, z) represents the expected haul by successful robbers (d = 0), which also depends on the duration of the robbery. D represents the *unobserved* disutility from apprehension. Notice that using haul as part of the objective function assumes a linear utility model, thus risk neutrality. Robbers are likely to organize several robberies each year, and if they weren't risk neutral one would have to know their expected increase in utility to evaluate a risk averse or risk loving version of Eq. 2 (Block and Heineke, 1975). Since we don't have information about robbers we have to assume risk neutrality, which might not be too far from the truth (Block and Gerety, 1995).

Robbers certainly choose which branch to target, and how. In other words, x and z are endogenous. 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). But once the choice is set, and bank robbers enter the bank both x and z are given, the bank robber has to choose how long to stay inside the bank.

The optimal duration of a bank robbery t^* , given specific characteristics of the bank and of the bank robbers, solves

$$-F'(t^*)[E(Y|t^*,\cdot)+D] + [1 - F(t^*|\cdot)]E'(Y|t^*,\cdot) = 0.^{6}$$
(3)

Solving the first order condition for the disutility of apprehension D gives

$$D(t^*, x, z) = \frac{1 - F(t^*|\cdot)}{F'(t^*|\cdot)} E'(Y|t^*, \cdot) - E(Y|t^*, \cdot)$$
$$= \frac{1}{\lambda(t^*|x, z)} E'(Y|t^*, x, z) - E(Y|t^*, x, z).$$
(4)

Estimates of $\lambda(t^*|x, z)$, $E'(Y|t^*, x, z)$ and $E(Y|t^*, x, z)$ provide the distribution of the disutility of apprehension, a decisive component of criminal behavior. It is clear that the

precision of the estimates depends on how precisely bank managers measure the duration of bank robberies t. Later, as a robustness check, I determine how robust the results are to measurement error in t.

4 Empirical Analysis of Preferences and Strategies of Bank Robbers

4.1 The Average and the Marginal Haul

According to Equation 4 the disutility of incarceration depends on the marginal haul E'(t), on the average haul E(t), and on the hazard rate of apprehension $\lambda(t)$. Figure 2 shows a locally smoothed regression with optimal bandwidth of the haul as a function of time (Cleveland, 1979). The conditional average haul appears to be linear in time, which is consistent with the typical technology used to rob a bank: i) enter the bank and walk to the teller, ii) ask the teller for the money, typically the teller's direct cash holdings, iii) collect and store the cash. Of all these actions the last is probably the most time consuming, and is likely to produce constant marginal cash returns with respect to time.

For these reasons I will model the haul using a linear regression, clearly a good approximation of the more flexible conditional mean. Linearity also has the advantage of delivering both $E'(t^*) = \beta$ and $E(t^*) = t^*\beta$ at once. Moreover, a liner regression allows me to estimate group specific marginal effects without suffering from the curse of dimensionality typical of more non-parametric methods. Using a linear model and allowing the slope of the haul with respect to t to depend on x the vector of the modus operandi x and of the branch characteristics z the estimating equation is:

$$y_i = \alpha + \beta'_w w_i + \beta_{t^*} t_i^* + \beta'_{t^*w} w_i t_i^* + \epsilon_i$$
(5)

where $w_i = (x_i \ z_i)$. Notice that the purpose of this equation is to provide the *best linear* predictor of the haul, without any considerations about causality. Indeed, most of the coefficients are likely to reflect the selection on ability, which is exactly what the model is supposed to isolate.

Table 5 presents the estimates of Eq. 5. Column 1 shows that when I do not control for any other characteristics of either the bank or the bank robbery, each additional minute spent robbing a bank increases the haul by an average of approximately 1,000 euro but, as we will see later, it also increases the probability of apprehension. In column 2 I allow the conditional mean E(t) but not the marginal effect E'(t) to depend on the characteristics of the bank robbery. Using firearms increases the average haul substantially (4,400 euro), and so does being masked (2,000 euro), which is probably a signal of ability and professionalism. Operating in groups, instead, seems to lower the per-capita haul. In column 3 these same variables are interacted with the duration of the bank robbery, allowing for differential slopes. All slopes stay positive, though having a firearm seems to be the only variable that increases the marginal effect significantly. In column 4 and 5 I add all the available controls, with and without interacting each control with the duration of the bank robbery. Column 6 shows that bank robberies in the South and in the Center of Italy have average hauls that are on approximately 1,500 euro larger than in the North. Isolated banks and banks with lower amounts of cash bring lower hauls (-300 euro and - 1,300 euro respectively). Smaller banks, that is banks with less than 5 employees, reduce the haul by an average of 300 euro. Security devices seem to payoff. Each additional security device reduces the average haul by 248 euro, and adding an additional characteristic to all security devices reduces the haul by 2,500 euro. A higher fraction of invisible security devices also reduces the expected haul. Banks that are guarded are subject to lower hauls, but the difference is not significantly different from zero. When I interact the duration with all these variables many of these coefficients

stop being significant (column 5). The slope does depend significantly on firearms (+1,600 euro), on the average number of characteristics per security device (-1500 euro), and small cash holdings (-800 euro). The last column presents the specification that I use to predict the haul and the marginal haul per minute. In order to have a robust estimate of the slope I condition on the interactions that are significantly different from zero.

4.2 The Hazard Rate of Arrest

But the benefits are only part of the story. Criminals are sometimes arrested, and might serve prison time. Figure 3 shows the estimated unconditional hazard rate, $\lambda(t)$, using the exponential hazard model and Cox's proportional hazard model.⁷ 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 the more constraint estimates based on the exponential model to more unconstraint ones. While I focus on the exponential model and the non-parametric Cox model, all hazard models lead to similar results.⁸

Table 6 shows how the same regressors that I used for E(t) influence $\lambda(t)$ based on both the exponential and Cox's proportional hazard model. In Cox model the coefficients do not depend on the baseline hazard, but the results are quite similar when a constant baseline hazard is used. In the first two columns of each model I control for the characteristics of the robbery and for the region, while the last columns additionally control for the characteristics of the bank. Focusing on the comprehensive regression, criminals who use firearms are less likely to get arrested, and so are robbers who work in groups. Robbers

⁷In Table 3 and in the hazard models successful robberies are treated as censored. Notice that the purpose is again to estimate the best predictor of the hazard rate and not to infer causality.

⁸The results are also robust to frailty models that allow for unobserved heterogeneity.

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. This is probably because more able robbers are more likely to target more "challenging" banks, but 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 the bank has a guard or not does not seem to matter.

4.3 The Disutility of Apprehension

After estimating E(t, x, z), E'(t, x, z), and $\lambda(t, x, z)$ Eq. 4 determines the disutility of apprehension. In order to compute the "yearly" disutility of apprehension I collected data on sentences related to bank robberies.⁹

4.3.1 The expected sentence length

Table 7 shows the summary statistics for the sample of 323 bank robberies attributed to 96 different bank robbers who were sentenced to jail between 2005 and 2007. This means that in our sample each robber has been judged 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 plea bargain. The other variables vary by robbery. In 22.5 percent of the cases robbers use firearms (versus 13.7 percent from the OSSIF data), in 57.2 percent they use masks (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 Euro, slightly lower than the total haul based

⁹In Italy there are no official statistics on prison time served by convicted bank robbers. The data refer to 96 bank robbers convicted in the Piedmont region. The corresponding 323 bank robberies were committed between 1993 and 2007.

on the banking data. Though the *modus operandi* of robbers that were sentenced are on average not exactly the same as that of the sample of robberies based on the bank data, the determinants of the sentence length shouldn't be biased.

Figure 4 shows the density of the yearly sentence length both using a histogram and a kernel estimator. The average sentence length is 3.4 years in prison. The distribution is skewed to the right. 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 apprehension, 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.

In order to determine the way the *modus operandi* shapes the expected sentence length in table 8 I regress the log-sentence length on whether the robber used firearms, was masked, or worked in groups. Using a firearm increases the sentence by approximately 50 percent after controlling for a set of variables (recidivism, used hostages, plead bargain, year, total number of robberies committed, total haul). Using a mask and working in groups has a smaller effect on the sentence. Working in groups increases the sentence length by approximately 30 percent, and being masked by 15 percent but without being statistically different from zero. This is likely to explain why so many robbers choose to work in groups and to wear a mask, while so few use a firearm. Only the use of firearms leads to strong and significant sentence enhancements.

4.3.2 The total and the yearly disutility of apprehension

Figure 5 shows for those criminals who were not arrested, and whose choice of t was probably unconstraint, the distribution of the total disutility of apprehension truncated at 250,000 euro. The yearly figures are truncated at 150,000 euro. An interesting feature of the distribution is its shape which resembles an earnings distribution. Since the value of staying out of jail is likely to depend on the robbers (illegitimate) earnings potential,

it follows that these earnings are distributed like legitimate earnings. It worth stressing that nothing in the model prevents the shape of the distribution from taking any other form or generating negative values of freedom. Indeed, for 10 percent of the robberies the model predicts negative disutilities of ending up in jail. This is entirely driven by those criminals who rob banks with a large average number of characteristics per security device. These criminals have such small marginal hauls that the disutility ends up being negative. These negative values of freedom can clearly be driven by factors that the model does not control for, like unobserved heterogeneity in expectations, or heterogeneity in risk aversion. Robbers that targeted banks with a large average number of characteristics per security device might have been unable to predict such small marginal hauls. Controlling for these kind of heterogeneities is an interesting avenue for future research.

The kernel densities show that dividing the total disutility by the expected sentence length reduces the heterogeneity in disutility. Table 9 shows that not only the variance but also the coefficient of variation gets smaller when controlling for the expected sentence length (-20 percent). Since expected sentences are likely to be measured with some noise (it is hard to know what robbers really expect the jail sentence to be), they could potentially explain an even larger share of the variation. The Table also shows that the distribution is highly right-skewed. As a consequence the median is small compared to the mean: 44,000 against 71,000 euro for the exponential model. The corresponding figures for the yearly disutility are 20,000 and 15,000 euro. These figures are implicitly assuming that robbers do not discount time. If they did, the yearly figures would be larger.

4.3.3 Disutility of apprehension: ability vs. deterrence

Robbers with different values of freedom target different banks, and use different *modus* operandi. In order to describe this selection I compute the derivative of the disutility with respect to the same variables that are related to the haul and the risk of arrest. Given that D differs across individuals so will its derivatives.

Table 10 shows the derivative of $\log D(t, x, z)$ with respect to duration t, modus operandi x, and branch characteristics z. In order to asses the level of significance of the derivatives I bootstrap the model a 100 times, computing 100 average derivatives (averaged over the bootstrap sample of robberies). The Table shows the average "average" derivative, its standard deviation, and the 5th and 95th percentile. Whenever the 5th and the 95th percentile have different signs the average derivative is not different from zero at the 10 percent level of significance.

The sanctioning rules (judges adjust sentences proportionally to the aggravation of the robbery) suggest to use the log value of freedom instead of the level.¹⁰ The observable characteristics of banks and bank robberies change the (log) value of freedom the way we 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 than "simple" robberies (*rapina semplice*). These deterrence effects are clearly visible in Table 10. The use of firearms leads to an increase in the disutility of apprehension of about 178 percent. Using masks and operating in group also leads to a sizable increase in disutility (65 to 80 percent). All these derivatives are significantly larger than zero. But these increases are considerably larger than the corresponding increase in the sentence length, suggesting that criminals that use firearms, work in groups, and mask themselves not only take longer sentences into account, thus increasing the *total* disutility, but are also of 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. Those that choose banks with less than 5 employees tend to be of higher ability, mainly because robberies in smaller banks are clearly less risky. Bank employees need to be monitored for the duration of the robbery, therefore greater

¹⁰Using the disutility of apprehension in levels gives very similar results.

the number of employees the riskier the robbery becomes. Security devices, instead, generate an ambiguous selection. While only the more able criminals select banks with more security devices, the same is not true for the average number of characteristics. The fraction of visible devices and whether the bank has a guard or not do not significantly alter the selection of criminals. The duration of the bank robbery is a clear predictor of the criminals value of freedom. Those who value freedom organize very short robberies, as the value of freedom of the criminals decreases by 12 percent for every additional minute spent robbing the bank. The model based on the Cox proportional model gives very similar results.

4.3.4 How does measurement error in duration change the distribution of D?

While measurement error in the duration is going to have no effect on a constant baseline, it will bias the marginal haul downwards. Some simulations that I performed show that while rounding a duration measured in seconds to the nearest or to the smallest minute has almost no effect on the coefficient of duration (chosen to have the same level of significance as in the actual data), rounding the duration randomly to one of the two nearest minutes induces a larger bias (-13 percent). The largest bias (-16 percent) arises when 10 percent of the durations are randomly set to be equal to 5 minutes. The relative bias of size m is going to induce a change in D that is equal to:

$$m\frac{\partial D_i}{\partial \log \beta_i} = m\frac{\beta_i(1 - t_i^*\lambda(t_i^*, x_i))}{\lambda(t_i^*, x_i)} \tag{6}$$

where $\beta_i = \beta_{t^*} t_i^* + \beta'_{t^*w} w_i t_i^*$ represents the individual slope with respect to t. Since $1 - t_i^* \lambda(t_i^*, x_i)$ is generally positive the bias reduces the estimated D. This can clearly be seen in Figure 6, where I plot the density of D assuming three different biases: a 5, 10, and 20 percent attenuation bias of the slope. Dealing with the attenuation bias reduces the fraction of negative disutilities of apprehension from 10.2 to 8.8 percent. The median and

the mean are clearly more sensitive to the measurement error. A 10 percent correction almost doubles the median (from 44,000 to 77,000 euro) and the mean (from 71,000 to 133,000). Adding another 10 percent correction increases the median and the mean by a relatively smaller amounts (77,000 to 108,000 and 133,000 to 195,000). The sensitivity to measurement error is quite high, which is why the following policy simulation is done allowing again for different degrees of measurement error.

4.3.5 How much deterrence is needed to eliminate bank robberies?

The structural model allows us to answer the following question: How much would we need to increase the disutility of jail to drive the number of bank robberies to zero? In terms of the model, one needs to determine the level of disutility that corresponds to an optimal duration that is equal to zero:

$$D(0, x, z) = \frac{1}{\lambda(0|x, z)} E'(Y|0, x, z) - E(Y|0, x, z).$$
(7)

 $\log D(0, x, z) - \log D(t^*, x, z)$ represents the percentage increase in disutility needed for robbers that use a modus operandi x, and rob banks of type z, in t^{*} minutes to drive the duration to 0.¹¹ Table 12 shows the distribution of the changes. Unlike the distribution of the disutility of apprehension these elasticities are less sensitive to measurement error. The 5th percentile shows that without correcting for measurement error in order to drive 5 percent of the sample to a duration of zero one needs a 3 percent increase in the total disutility of jail, or equivalently the same increase in sentence length. Controlling for measurement error the change in penalty needed is almost unchanged. In order to reduce the bank robberies by a quarter the penalties would have to increase by between 6 and 9 percent, depending on the degree of the bias. To curb robberies by one-half penalties would have to increase by between 11 and 17 percent. In order to almost eliminate

¹¹When the exponential model is used the hazard rate does not depend on t and $\lambda(0|x,z) = \lambda(x,z)$.

bank robberies (-95 percent) the sanctions would have to increase by 78 percent in the absence of measurement error and by 48 percent if the measurement bias was equal to 10 percent. Overall, the estimated model predicts criminal behavior to be highly responsive to changes in the sanctioning system. Given the assumption of risk neutrality, robbers would be equally responsive to changes in the likelihood of arrest.

The data allow us to go even further and explore which robbers are more likely to respond to increased sanctions. Table 13 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 to 0. Values below the median signal high responsiveness to sanctions (the corresponding average log change in disutility is 9 percent), values above the median low responsiveness to sanctions (the corresponding average log change in disutility is 46 percent). A pretty clear picture emerges from the table. Professional robbers, robbers with higher values of freedom (133,000 versus 31,000 euro), are also more responsive to sanctions. In particular, essentially all robbers that use firearms belong to the high responsiveness category. Masked robbers are also considerably more likely to be highly responsive (64 versus 27 percent). This means that harshening sanctions would mostly deter those robbers that responsible for the largest losses. The amateur robbers would most likely keep on trying to rob banks. It is worth noticing that in the US, where sanctions are definitely more sever, bank robberies are believed to be mostly the work of amateurs (Weisel, 2007).

5 Conclusions

Based on unique data on individual bank robberies perpetrated in Italy between 2005 and 2007 this paper isolates the criminals' disutility of apprehension. The grand majority of criminals face relatively low disutilities of apprehension while a few face very high ones. The shape of the distribution resembles the shape of an earnings distribution. This skewness suggests that anti-poverty measures targeted towards potential low-skilled criminals might lead to a great reduction in the number of bank robberies.

Simulating relative changes in the value of freedom that would bring the optimal duration of bank robberies to zero suggests that deterrence is high, and that the most responsive robbers are the more professional ones, meaning those that have a high disutility of ending up in jail. These tend to rob banks using firearms, masks, and work in teams. They are also more likely to target the right banks, the ones with higher cash holdings but with fewer employees.

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Figure 1: Time series of Italian Robberies and of the Number of Casualties





Notes: The solid line represents the linear regression, the dashed one a locally smoothed regression with optimal bandwidth. The left panel shows the regression lines with duration truncated at 30 minutes, the right one truncates the duration at 10 minutes.



Figure 3: The Estimated Hazard Rate

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



Figure 4: Density of the Sentence Duration (in Years)



Figure 5: The Distribution of the Conditional Value of Freedom

Notes: The upper panels show the distribution of the total disutility of jail, the lower ones the corresponding yearly figures assuming a discount factor of one. These estimates are based on successful robberies only.



Figure 6: The Distribution of the Conditional Value of Freedom Depending on the Measurement Error

	Total Robberies	R. per Branch (in $\%$)		Total Robberies
Andorra	0	0	Japan	133.29
Australia	119	2.54	Liechtenstein	0
Belgium	117.43	1.37	Lithuania	12.29
Bulgaria	1	0.32	Luxembourg	2.14
Canada	827.71	14.1	Malta	0.71
Croatia	27.43	2.45	Monaco	0
Cyprus	6.57	0.91	New Zealand	25.14
Czech Republic	66.29	4.08	Norway	11.86
Denmark	160.14	7.91	Poland	72.71
Estonia	1.71	0.69	Portugal	97.29
Finland	8.71	0.53	Slovak Republic	13.57
France	639.29	2.28	Slovenia	11.57
Germany	837.71	1.96	Spain	523.43
Greece	143.57	3.68	Sweden	38.86
Hungary	33.29	1.03	Switzerland	16.29
Iceland	2.71	1.66	The Netherlands	77.14
Ireland	64.57	5.22	Turkey	83.86
Italy	2770.86	8.67	UK	191.86

Table 1: Number of Bank Robberies across the World

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

	P(success)	Av. Haul		P(success)	Av. Haul
Australia	0.56	14227	Italy	0.9	20183
Belgium	0.57	47434	Japan	0.29	
Bulgaria	1	12880	Lithuania	0.55	63545
Canada	0.97	3011	Norway	0.5	807
Croatia	0.87	25592	Poland	0.71	5502
Cyprus	1	35548	Portugal	0.89	8643
Czech Republic	0.75	11053	Slovak Republic	0.86	11200
Denmark	0.93	22023	Slovenia	0.7	2591
Estonia	1	4470	Spain	0.92	16065
Finland	0.67	804795	Sweden	0.71	18608
France	0.79	14331	Switzerland	0.65	90065
Germany	0.76	32417	The Netherlands	0.41	60380
Greece	0.89	29307	Turkey	0.73	4848
Hungary	0.5	17003	UK	0.6	32827
Ireland	0.82	8626			

Table 2: Probability of Success and Average Haul across the World

Source: European Banking Federation for the year 2006.

	Beg.			Survivor	Std.
Time	Total	Arrested	Successful	Function	Error
1	6136	27	380	0.9956	0.0008
2	5729	78	1298	0.982	0.0017
3	4353	116	1947	0.9559	0.0029
4	2290	35	586	0.9413	0.0038
5	1669	60	833	0.9074	0.0056
6	776	4	84	0.9027	0.0061
7	688	5	57	0.8962	0.0067
8	626	1	61	0.8948	0.0068
9	564	0	13	0.8948	0.0068
10	551	29	214	0.8477	0.0107
11	308	0	6	0.8477	0.0107
12	302	0	11	0.8477	0.0107
13	291	2	14	0.8418	0.0114
14	275	0	3	0.8418	0.0114
15	272	10	64	0.8109	0.0146
16	198	1	4	0.8068	0.0151
17	193	1	2	0.8026	0.0156
18	190	5	0	0.7815	0.0178
19	185	0	4	0.7815	0.0178
20	181	9	63	0.7426	0.0211
22	109	0	2	0.7426	0.0211
23	107	0	3	0.7426	0.0211
25	104	0	37	0.7426	0.0211
27	67	0	1	0.7426	0.0211
28	66	0	1	0.7426	0.0211
29	65	0	1	0.7426	0.0211
30	64	4	60	0.6962	0.0299

Table 3: Duration of bank robberies

Sample	W	hole	duration	duration $\leq 3min$		duration $> 3min$	
	Mean	SD	Mean	SD	Mean	SD	
Arrested	6.33%	24.35%	6.28%	24.27%	6.43%	24.54%	
Duration of the robbery (in minutes)	3.24	1.40	2.44	0.66	4.93	1.01	
Total haul	13,778	$24,\!291$	$11,\!559$	$14,\!959$	18,469	36,505	
Haul	$7,\!879$	11,772	7,025	8,736	$9,\!684$	$16,\!294$	
Firearms	0.14	0.34	0.12	0.33	0.16	0.37	
Two robbers	0.52	0.50	0.51	0.50	0.56	0.50	
Three or more robbers	0.14	0.35	0.11	0.32	0.19	0.40	
Masked robbers	0.43	0.50	0.43	0.50	0.43	0.50	
Center Italy	0.21	0.41	0.20	0.40	0.22	0.42	
South Italy	0.28	0.45	0.27	0.45	0.30	0.46	
Guarded	0.08	0.27	0.07	0.26	0.09	0.28	
Isolated branch	0.25	0.43	0.25	0.43	0.25	0.43	
Bank with little cash	0.63	0.48	0.62	0.48	0.65	0.48	
Bank with less than 5 employees	0.51	0.50	0.50	0.50	0.53	0.50	
Number of Security Devices	5.62	1.17	5.62	1.16	5.62	1.20	
Average Number of Characteristics per	1.26	0.38	1.27	0.39	1.24	0.36	
% of invisible devices	0.67	0.16	0.68	0.16	0.66	0.15	
N.obs.	4,5	549	3,	088	1,	461	

 Table 4: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)
		~ /	E E	Iaul		
Duration of the robbery (in minutes)	1,060.50***	1,143.52***	794.44**	1,076.88***	5,231.72***	3,144.16***
Firearms	(187.59)	(186.80) $4,120.12^{***}$	(312.02) -2,231.94	(186.75) $4,021.45^{***}$	(1,623.57) -1,593.53	(844.83) -2,049.87
Two robbers		(816.63) -2,352.91***	(1,725.27) -2,052.24*	(835.85) -2,595.30***	(1,833.91) -2,127.17*	(1,752.52) -2,607.55***
Three or more robbers		(379.44) -2,653.21***	(1,196.41) -1,195.59	(373.16) -3,007.34***	(1,115.56) -197.08	(370.07) -3,022.54***
Masked robbers		(651.89) 1,653.62***	(1,623.08) 94.02	(676.75) 1,362.43***	(1,705.74) 395.61	(664.21) 1,301.93***
Center Italy		(367.47)	(1,245.98)	(365.36) 1,600.26***	(1,072.45) 1,436.98	(368.61) 1,519.66***
South Italy				(398.46) 1,650.71***	(1,603.83) 459.51	(398.25) 1,644.98***
Isolated branch				(478.68) -379.34	(1,115.93) -737.19	(474.10) -415.60
Bank with little cash				(353.67) -1,334.83***	(1,512.19) 1,352.32	(353.01) 1,458.19
Bank with less than 5 employees				(425.81) -368.68	(1,282.04) 266.59	(1,356.84) -381.47
Number of Security Devices				(382.65) -248.72**	(1,097.37) 288.60	(380.83) -285.14**
Average Number of Characteristics per Security Device				(123.36) -2,493.54*** (386.24) 1.054.26**	(395.90) 2,246.07** (1,001.13) 2,408.02	(123.91) 1,606.60 (1,047.02) 2,222,48**
Guarded				(957.67) -345.45 (800.87)	(2,718.31) -7,069.84* (2,825.18)	(969.29) -557.97 (706.10)
Interaction				(800.87)	(3,823.18)	(790.19)
Firearms			$1,878.95^{***}$		$1,633.29^{**}$	$1,798.59^{***}$
Two robbers			(004.30) -115.07 (420.25)		(711.49) -140.35 (206 50)	(009.54)
Three or more robbers			(429.25) -449.20 (5.67.10)		(390.39) -855.85	
Masked robbers			(567.10) 462.44 (427.62)		(603.88) 264.77 (272.92)	
Center Italy			(437.02)		(373.23) 25.79 (500.22)	
South Italy					(508.33) 336.39 (412.40)	
Isolated branch					(412.49) 88.81 (514.99)	
Bank with little cash					(514.22) -850.41*	-881.88*
Bank with less than 5 employees					(466.44) -189.01	(477.66)
Number of Security Devices					(390.55) -172.71 (122.02)	
Average Number of Characteristics per Security Device % of invisible devices					(132.92) -1,562.46*** (358.76) -1,430.97	$-1,369.87^{***}$ (356.20)
Guarded					(909.33) 2,030.87	
Observations R-squared	$4549 \\ 0.016$	$4549 \\ 0.045$	$4549 \\ 0.052$	$4549 \\ 0.058$	(1,308.14) 4549 0.077	$4549 \\ 0.070$

Table 5: Linear Regressions of the Per-Capita Haul

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

	(1)	(2)	(3)	(4)	(5)	(6)
]	Exponentia	ıl	Co	x Proportio	onal
Firearms	-0.38*	-0.37*	-0.42**	-0.40**	-0.39*	-0.44**
	(0.20)	(0.20)	(0.21)	(0.20)	(0.20)	(0.21)
Two robbers	-0.48***	-0.47***	-0.47***	-0.55***	-0.54***	-0.54***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Three or more robbers	-0.42**	-0.44**	-0.48**	-0.54***	-0.55***	-0.60***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Masked robbers	-0.63***	-0.62***	-0.65***	-0.61***	-0.60***	-0.64***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Center Italy		-0.18	-0.19		-0.18	-0.19
		(0.17)	(0.17)		(0.17)	(0.17)
South Italy		0.08	0.07		0.06	0.02
		(0.14)	(0.14)		(0.14)	(0.14)
Isolated branch			-0.04			-0.04
			(0.15)			(0.15)
Bank with little cash			-0.03			-0.03
			(0.13)			(0.13)
Bank with less than 5 employees			-0.36***			-0.40***
			(0.12)			(0.12)
Number of Security Devices			-0.11**			-0.11**
			(0.05)			(0.05)
Average Number of Characteristics			-0.04			0.02
per Security Device			(0.16)			(0.16)
% of invisible devices			-0.11			-0.10
			(0.36)			(0.36)
Guarded			0.12			0.19
			(0.23)			(0.23)
N.obs.	4549	4549	4549	4549	4549	4549

Table 6: Hazard Models

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

Variable	Mean	Std. Dev.	Min.	Max.	Ν
	Ir	ndividual-leve	l inform	ation	
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
	Ι	Robbery-level	informa	tion	
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

 Table 7: Summary statistics

	(1)	(2)	(3)	(4)
		log-S	entence	
Firearms	0.50^{***}	0.36**	0.39^{***}	0.28^{***}
	(0.09)	(0.16)	(0.10)	(0.09)
Masked	0.10	0.08	0.07	0.03
	(0.09)	(0.08)	(0.08)	(0.08)
Group robbery	0.25^{***}	0.14	0.20^{**}	0.09
	(0.09)	(0.11)	(0.08)	(0.08)
Number of robberies		0.02		0.03**
		(0.01)		(0.02)
Recidivist		-0.03		-0.03
		(0.11)		(0.08)
Hostages		0.05		-0.10
		(0.10)		(0.18)
Total haul		0.00*		0.00
		(0.00)		(0.00)
Plea bargain		-0.21*		-0.27***
		(0.12)		(0.08)
Year	-0.00	-0.01		-0.02
	(0.03)	(0.02)		(0.02)
Observations	316	316	95	94
R-squared	0.331	0.431	0.197	0.361

 Table 8: Determinants of the Sentence Length

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

	% Negative	Mean	St. Dev.	C. Var.	P10	P25	P50	P75	P90
			Tot	al disutilit	Jy				
Exponential	0.102	71.25	93.09	1.31	-0.35	19.98	44.54	87.05	178.93
Cox	0.118	66.49	128.40	1.93	-2.45	11.36	32.46	75.50	162.64
			Year	ly disutili	ty				
Exponential	0.102	20.09	21.28	1.06	-0.12	7.41	15.26	27.66	46.76
Cox	0.118	18.69	30.75	1.65	-0.88	4.08	11.21	23.60	46.87
Ν			40	54					

Table 9: Conditional Heterogeneity in D

	Average	SD	P5	P95
Duration of the bank robbery	-0.12	0.02	-0.15	-0.09
Firearms	1.78	0.41	1.12	2.43
Two robbers	0.68	0.16	0.43	0.94
Three or more robbers	0.65	0.21	0.28	0.99
Masked robbers	0.80	0.16	0.56	1.12
Center Italy	0.20	0.21	-0.18	0.53
South Italy	-0.16	0.17	-0.44	0.11
Isolated branch	0.09	0.20	-0.22	0.42
Bank with little cash	-0.90	0.36	-1.50	-0.28
Bank with less than 5 employees	0.46	0.14	0.25	0.71
Number of Security Devices	0.23	0.12	0.04	0.45
Average Number of Characteristics per Security Device	-0.81	0.16	-1.07	-0.53
% of invisible devices	0.27	0.45	-0.44	0.93
Guarded	-0.09	0.33	-0.58	0.42

Table 10: log-Value of Freedom changes

Table 11: Measurement Error in Duration and D

	% Negative	Mean	St. Dev.	C. Var.	P10	P25	P50	P75	P90
No correction	0.102	71.25	93.09	1.31	-0.35	19.98	44.54	87.05	178.93
5% correction	0.095	102.21	143.58	1.40	1.53	29.01	62.08	116.11	241.05
10% correction	0.093	133.18	196.39	1.47	3.17	37.37	77.06	144.29	315.37
20% correction	0.088	195.11	304.13	1.56	7.13	53.84	108.24	199.19	445.27

	Mean	St. Dev.	P5	P25	P50	P75	P95
No correction	0.27	0.44	0.03	0.09	0.17	0.31	0.78
5% correction	0.22	0.29	0.03	0.08	0.14	0.25	0.59
10% correction	0.19	0.24	0.03	0.07	0.13	0.21	0.48
20% correction	0.16	0.21	0.03	0.06	0.11	0.18	0.38

Table 12: Change in $\log D$ that Corresponds to $t^*=0$

Table 13: High and Low Responsiveness

Below median $\Delta \log D$	Above median $\Delta \log D$
$high\ responsiveness$	$low\ responsiveness$
Mean	Mean
0.09	0.46
133.02	30.84
2.88	3.66
0.31	0.00
0.58	0.48
0.16	0.12
0.64	0.27
0.28	0.17
0.22	0.31
0.26	0.25
0.49	0.74
0.51	0.52
5.75	5.59
1.13	1.22
0.70	0.66
0.09	0.08
	Below median $\Delta \log D$ high responsiveness Mean 0.09 133.02 2.88 0.31 0.58 0.16 0.64 0.28 0.22 0.26 0.49 0.51 5.75 1.13 0.70 0.09