Social Interactions and Crime Prevention

Very Preliminary and Incomplete - Please Do Not Circulate or Cite

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Abstract

Using unique data from Sicily we investigate the presence of social interactions in the behavior of firms to fight organized crime. We develop a model of social interactions that analyzes the impact of social influences on the decision of firms to refuse to pay the mafia's protection fee and join a Palermo based NGO, called AddioPizzo. We provide estimates of social interactions using duration analysis and test the predictions of the theory. Preliminary results highlight the major role of social interactions in explaining firms' behavior.

Keywords: organized crime, social interactions, duration models.

JEL Classification Codes: C40, D01, O33

1 Introduction

Organized crime can be viewed as the world's largest social network and constitutes one of the biggest and most complex challenges that many societies face around the world. It is well known that this problem is especially prevalent in several regions of Italy such as Sicily, Calabria and Apulia. Recent empirical work has documented the substantial adverse effect of organized crime on the economy (e.g., Pinotti, 2015). While policy makers and organized groups have recognized the importance of the mobilization of civil society in the fight against organized crime, there is no formal econometric work yet that assesses the importance of such social behavior.[1] Therefore, we believe that identifying and quantifying the role of social interactions to mobilize the society is critical for designing policies that prevent organized crime.

The objective of this project is to study the role of social interactions in the fight against organized crime. Since 2005, a new way of fighting the organized crime has evolved in Palermo, Italy. *Addiopizzo* (AP), a local NGO, organized and encouraged an anti-mafia rebellion by publicly announcing the firms that refuse to pay the mafia's protection fee.[2] The idea is that the consumers will reward the AP firms and decline to patronize firms that participate in the Sicilian mafia's pizzo (protection money) system. This creates incentives for firms to join the AP and therefore reduce their demand for protection from mafia. As a result mafia will be weakened and eventually disappear. To us, this suggests that the decision to the AP can be viewed as a technology adoption problem. Therefore, we can interpret the social interactions as the positive feedback of external spillover effects from the fraction of firms having already joined the AP association in the profit function to each firm

[1] Lavezzi (2014) who discusses policies to combat organized crime using economic analysis makes a similar point.

[2] *Addiopizzo* means "farewell to *pizzo*": the Sicilian definition of the money extorted by *Cosa Nostra*.

that has joined the AP ("adopted" the new technology).

There is now a large body of work in the literature that considers the role of social interactions in economic behavior (e.g., Brock and Durlauf (2001a,b), Blume, Brock, Durlauf, and Jayaraman (2015)). Durlauf and Ioannides (2010) and Benhabib, Bisin, and Jackson (2011a,b) provide recent surveys of various classes of social interaction models and their empirical applications. By social interactions in the present context, we refer to interdependencies among firms in a neighborhood in which the agent's behavior (preferences, beliefs, and constraints) is directly affected by the characteristics and choices of others rather than indirectly through the intermediation of markets and enforceable contracts. A key feature of social interaction models is that they can generate multiple equilibria and as a consequence a small change in fundamentals may lead to large differences in group behavior. In our context, we can interpret the social interactions as the positive feedback of external spillover effects from the probability measure that describes the beliefs a firm possesses about behaviors of others in the group concerning the decision to join AP and cut ties with the mafia or continue to "buy" protection services from the mafia.

Our work is related to several papers that investigate the presence of social interactions. Glaeser, Sacerdote, and Scheinkman (1996) study how social interactions among individuals can explain the variation in crime rates across large American cities. Sirakaya (2006) studies the risk factors for recidivism using a Cox proportional hazard model that incorporated social interactions among probationers. de Paula (2009) considers the timing of desertion by soldiers using a simultaneous duration model with multiple decision makers and interdependent duration. Brock and Durlauf (2010) study the impact of social influences on adoption decisions for an environment of perfect foresight adopters. We contribute to the above literature in three important ways. First, to our knowledge, this is the first study that considers the presence of social interactions as a prevention device for organized crime.

One interpretation of the role of the AP association is that it represents a new "technology", which was made available to the businesses and consumers of Palermo. Second, we develop a model social interactions in the spirit of Brock and Durlauf (2010) and test the empirical implications of the theory. According to theory social interactions can produce jumps in the adoption rates and pattern reversals in which firms' characteristics suggest they would adopt earlier than others but nevertheless adopt later. Third, we consider a novel dataset that includes firm-level budget data as well as census data.[3] Fourth, we consider the impact of policies that aim at reducing organized crime on non-organized crime.

Our empirical investigation proceeds as follows. First, we investigate the effect of social interactions on the delay of joining AP within a neighborhood using hazards regression that allows for unobserved heterogeneity. The neighborhood is defined by the location of each firm proxied by the zip code or administrative district. Following Manski (1993), we distinguish between three types of social interaction effects: endogenous effects, contextual effects, and correlated effects. Endogenous effects occur when the tendency of a firm to join AP depends on the group behavior while the choices are simultaneously determined. Exogenous or contextual effects occur when the decision of the firm depends on the exogenous characteristics of the group. Correlated effects occur when agents in the same group tend to behave similarly because they have similar characteristics or face similar institutional environments. This distinction is important because endogenous social interactions possess a social multiplier that works in the same way as the Keynesian multiplier and magnifies the disparities in the average group behavior across groups. Therefore, in our context, a firm's likelihood to join will affect the likelihood of other firms to join by more than its share. This implies that the impact of a policy that functions through social interactions will have different consequences on organized crime from a policy that affects the exogenous

[3]Our dataset extends the dataset of Battisti, Lavezzi, Masserini, and Pratesi (2015) in many important respects.

characteristics of a firm. Preliminary results show that the percentage of firms that already joined in the zip code or district of firm i is the most important determinant of the decision of the firm i to join the association and cut ties with the mafia.

Next, we plan to investigate the empirical implications of the theory on adoption curves. In particular, we consider the possibility of jumps in the adoption rates and pattern reversals. Finally, we consider the role of social interactions in several outcome variables of the firms including firm-life and profits.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 develops an economic model of social interactions. Section 4 describes the empirical implementation using hazard models and presents the results. Finally, Section 5 concludes.

2 Data

2.1 A brief background on Addiopizzo

In the night of June 29th, 2004, a few young activists founded AP and flooded the walls of Palermo with stickers carrying the slogan: *"A whole people who pays the pizzo is a people without dignity"*, to provoke a reaction of the civil society against the Mafia.

In 2005 AP launched a campaign to spread this message of resistance which brought, in May 2006, to the publication in the local press of a list of more than 100 businesses who publicly denounced the *pizzo* system, claiming their refusal to pay.[4] The public list of AP-firms suggest consumers where to shop if they wish to: "pay those who do not pay". Participating stores signal their membership to AP by placing a sticker at the entrance of

[4] The current list can be consulted in the AP website: `http://www.addiopizzo.org`.

their premises.[5]

2.2 Data Description

Our dataset includes both AP-firms and a control group of non-joiners for the period 2001-2013. We consider 2005 as the base year, which was the year that the AP actively started its anti-mafia campaign.[6] We matched the information provided by the AP (firms' identity and firms' date of joining) with data from the administrative records available in the Italian Chamber of Commerce system and provided by CERVED. The AP group includes both private and limited-liability companies. The control group is a random sample of both types of firms, extracted from the CERVED dataset, stratified by the distribution in the AP group of firms' birth year.[7] In this work we focus on the firms operating within the municipality of Palermo, representing 74% of the AP-firms at the date of collection of the data.

The unit of analysis of our study is the delay in joining the AP, which is defined as the time it takes for each firm to join since 2005. If a firm was established after 2005, the time spell starts from the year that it started doing business, instead of 2005.[8]

In terms of covariates we have collected balance sheet data pertaining mostly to the limited-liability firms including total assets, bank loans, and personnel costs. In addition to the firm-level data, we collected data on the neighborhoods in which firms are located.[9] In particular, for all neighborhoods we collected data on socio-economic conditions from the 2001 Census, and data on the population of firms in the period of interest. Table 1 provides

[5]For more details on AP and references, see Battisti, Lavezzi, Masserini, and Pratesi (2015).

[6]The list of joiners was provided by Addiopizzo.

[7]Specifically, we distinguished firms established before 2005, exposed to the existence of AP for a limited part of their life, from firms established after 2005, that were exposed to AP since their creation.

[8]The delay is computed as $t - 2005, \tau_i \leqslant 2005$ and $t - \tau_i, \tau_i > 2005$ and ranges from 0 to 8.

[9]We considered both the classification by the 32 zip codes and by the 25 administrative districts of Palermo.

more details on the variables.

Our final dataset includes 315 AP-firms (188 with balance-sheets data, 127 without) and 1017 firms in the control group (579 with balance-sheets data, 437 without).[10] Note that the time dimension can be exploited only for the firms with balance sheets data as for the others only qualitative information is available and no time variation of firms' quantitative characteristics (e.g., capital stock, turnout, etc.) can be measured. This leads us to consider both a cross-section and an annual panel.

Table 2 reports summary statistics. AP-firms appear to have on average a higher share of other AP-firms in their neighborhood, have on average a higher size, a higher level of bank debts, a higher human capital embodied, and have in the same neighborhood an average higher share of human capital embodied in other firms. No appreciable differences appear in the variables related to the firms' age.[11]

3 The Model

We start by developing an economic model of adoption with social interactions when the firms are members of a common group g, $g = 1, ..., G$ along the lines of Brock and Durlauf (2010). In each group there are n_g firms. In each period s, firm i in group g takes a decision $\omega_{i,g}$, whether to adopt the new "technology" (i.e., join the AP) or not (i.e., stay under the protection of the mafia). We assume that a firm i with a vector of characteristics $\mathbf{Z}_i$ chooses an adoption time t, in order to maximize the present discounted value of current and future

[10]The number of controls was chosen to have approximately three controls for each firm in the sample, a ratio which is common in case-control studies. See, e.g. Dicker (2002).

[11]Battisti, Lavezzi, Masserini, and Pratesi (2015) find that firms' assets are negatively correlated with the probability to join, while personnel costs are positively correlated. Firm's age is also negatively correlated with the probability to join AP while bank debts have no significant effects.

profits

$$\Pi(t, \mathbf{Z}_i) = \int_t^\infty exp\,(-rs)\,\pi(\mathbf{Z}_i, m_i^e(\omega_{-i,g}, s))ds - exp(-rt)C, \tag{1}$$

where r is the discount rate, C is the cost of adoption, and $\pi(Z_i, m_i^e(\omega_{-i,g}, s))$ is the expected profit at time s. A key assumption is that the profit function depends on the expected fraction of adopters $m_i^e(\omega_{-i,g}, s)$ that describes the beliefs firm i possesses about behaviors of others in the neighborhood of the firm.

- To be completed -

4 Empirical Implementation

4.1 Hazard Model with Social Interactions

In this section we investigate how social interactions affect the probability of the event that a firm decides to join AP and hence, its relationship with the mafia comes to an end.[12] That is, the probability of transition from one state (mafia state) to another (AP state) depends on social interactions. Put differently, we are interested in investigating whether the "waiting" time during which a firm remains under the protection of mafia is affected by social interactions.

We assume that firms $i = 1, ..., n_g$ enter the mafia state at time zero and each firm

[12] We are treating joining AP as signaling the noncompliance with paying the Mafia. However, while joining AP is observable, not paying the Mafia is not. To join AP, firms must sign a declaration of non compliance with extortionary requests but we are not able to control for the firms' truthful disclosure of information. As discussed by Vaccaro (2012, p. 7), firms can be "double-game" players and choose to join an anti-racket organization to hide their actual connections with organized crime. Indeed, some evidence shows that mafia bosses suggested to strategically join anti-mafia organizations to this purpose. See Vaccaro (2012, p. 7). AP, however, closely monitors the joiners and has already expelled some "double-game" players. The number of cases seems very limited, as confirmed by personal communication. Therefore, in this paper we posit that joining AP implies refusing to pay the *pizzo*, while not joining implies complying with extortionary requests and staying under Mafia "protection".

experiences a single spell in this state. Let the delay in joining the AP be the duration of this spell denoted by the random variable T_i and let its realization be denoted by t_i, which takes a value in $\{1, 2, ..., \bar{t}\}$, where $\bar{t}$ is the maximum value of the delay in the data. We are interested in firm's i conditional cumulative distribution function of T_i

$$F_{T_i|\cdot}(t_i) = P(T_i \leq t_i | \mathbf{X}_i, \mathbf{Y}_g, m^e_{i,g}, v_g), \tag{2}$$

where $\mathbf{X}_i$ is a $p_X \times 1$ vector of firm-specific (exogenous) characteristics, $\mathbf{Y}_g$ is a $p_Y \times 1$ vector of neighborhood characteristics, and $m^e_{i,g}$ denotes i's subjective moments about the other firms that join AP by some duration τ in i's neighborhood, g. We assume that the neighborhood is given by the zip location or administrative district of the firm. Similarly, we can define the conditional density of T_i, $f_{T_i|\cdot}$. Note that X_i and Y_g may contain time-varying variables but for simplicity we suppress the time index. Then the conditional survival function of T_i is defined as $S_{T_i|\cdot}(t_i) = 1 - F_{T_i|\cdot}$, which gives the probability that a transition has not occurred by duration t_i. v_g captures unobserved group-level heterogeneity. We model this type heterogeneity using zip code or district fixed effects.

We focus on the rate at which a firm leaves the state of mafia at duration t_i given that it has not done so yet. Specifically, conditional on $\mathbf{X}_i$, $\mathbf{Y}_g$, $m^e_{i,g}$, the probability that the duration of mafia state is completed at t_i given it has not been completed before t_i is defined by the hazard function

$$\psi(t_i | \mathbf{X}_i, \mathbf{Y}_g, m^e_{i,g}, v_g) = P(T_i = t_i | T_i \geq t_i, \mathbf{X}_i, \mathbf{Y}_g, m^e_{i,g}, v_g) = \frac{f_{T_i|\cdot}(t_i)}{S_{T_i|\cdot}(t_i)} \tag{3}$$

The value of the hazard function for specific t_i is called the hazard rate. The hazard rate is a measure of risk in the sense that higher hazard rates correspond to higher risks of transitioning out of the mafia state therefore implying shorter delays.

For firm i, the hazard function of the random variable T_i evaluated at the duration t_i is specified as follows

$$\psi(t_i|X_i, Y_g, m^e_{i,g}, v_g, \epsilon_i) = \epsilon_i \psi_0(t_i) exp(\alpha' \mathbf{X}_i + \beta' \mathbf{Y}_g + \gamma m^e_{i,g} + v_g), \tag{4}$$

where $\psi_0(t_i)$ is the time dependent part known as the baseline hazard function that describes the countries' risk for transitioning if their risk was independent of their characteristics. This specification allows only the level of the hazard function to differ across firms. ϵ_i is a random effect with mean zero and a distribution that does not depend on the observed covariates to capture the unobserved heterogeneity of frailty along the lines of Heckman and Singer (1984) who propose a semiparametric estimator that does not require a specific distribution for ϵ_i. When we switch off the unobserved heterogeneity we obtain the classical Cox proportional hazards model. The objects of interest are the coefficients α, β, and γ that measure the exogenous effects, the correlated effects, and the endogenous social interactions, respectively. For example, a unit increase in the expected fraction of adopters increases or decreases the hazard of ending the mafia state by $exp(\gamma) - 1$ percentage points depending on whether the γ coefficient is positive or negative, respectively. Following Brock and Durlauf (2001a) we assume that firms have rational expectations and hence $m^e_{i,g} = m_{i,g} = \int dF_X \sum_{i \in g(i)} F(\tau|\mathbf{X}_i, \mathbf{Y}_g, m^e_{i,g}, v_g)$, where F_X is the probability distribution of individual characteristics within neighborhood g.

One advantage of our methodology is that the identification issues that arise in linear-in-means models (Manski (1993)) are avoided due to the nonlinear nature of the model (Brock and Durlauf (2001a)). A caveat of the above methodology is that firm's location (by zip or district) is not exogenous but it is likely to be endogenous. We address this challenge using a sample selection method along the lines of Blume, Brock, Durlauf, and Jayaraman (2015).

4.1.1 Results

In Table 3 we present our benchmark results for hazards model in equation (4) using the panel dataset. In columns (1)-(3) we present estimations of a simple specification where the hazard function only depends on the expected fraction of adopters in firm's i zip code but differ in the way we model unobserved heterogeneity. In column (1) we do not allow for any type of heterogeneity. In column (2) we allow for unobserved group-level heterogeneity using zip codes fixed effects while in column (3) we allow for unobserved firm specific heterogeneity using a discrete frailty distribution following Heckman and Singer (1984). In columns (5)-(7) we add firm's characteristics and in column (8) we further add the group-level (zip-code) characteristics to capture correlated effects. Columns (4) and (8) consider social interactions in a district rather than a zip code using the simplest and the largest model.

We find that the expected fraction of adopters in a zip code is positive and significant at least 5% in all specifications. In all cases we find that the coefficient of the expected fraction of adopters, which captures the endogenous social interactions, is positive and significant at 1%. For example, in the case of column (8), a unit increase in the expected fraction of adopters increases the hazard of ending the mafia state by 1.8 percentage points. Interestingly, we observe higher coefficients in the case of districts. A unit increase in the expected fraction of adopters increases the hazard of ending the mafia state by 4.5 percentage points. This evidence suggests the presence of endogenous social interactions.

In terms of the other covariates we find that personnel costs and age play a positive role in increasing the hazard of ending the mafia state but their size is much smaller than the effect of the expected fraction of adopters. Similarly, the correlated effects modeled by zip-level or district-level characteristics have a smaller impact on the hazard than the endogenous social interactions. In particular, in the case of zip-level characteristics we only find a positive and significant coefficient (at 10%) for the average revenues. In the case of zip-level characteristics we find significant a positive and significant coefficient (at 5%) for the average revenues as well as a negative coefficient for personnel costs (at 10%).

In Table 4 we present some additional results using the cross-section dataset. Our main finding about the important role of endogenous social interactions is present in the cross-section. Interestingly the effect of endogenous social interactions appears to be much stronger. For example, in the case of column (4), a unit increase in the expected fraction of adopters increases the hazard of ending the mafia state by 18.3 percentage points. In terms of the other variables we find that while personnel costs and revenues increase the hazard of ending the mafia state bank loans decrease it.

4.2 Discontinuities in the Adoption Curve and Pattern Reversal

Our framework allows us to empirically test the predictions of Brock and Durlauf (2010). They show that when social interactions are absent, both the firm's profit function and its best response function are monotonically increasing in X_i but when social interactions are absent both may exhibit non-monotone behavior. At the equilibrium the interaction of this non-monotone behavior with the assumption of decreasing productivity over time implies discontinuities in the adoption curve. In this case we would expect to see the presence of threshold effects due to social interactions $q_i = \pi^e_{n(i)}$. While the absence of a discontinuity does not imply that social interactions are absent, the discontinuity occurs when the strength of the effect of social interactions is large. However, the discontinuity in the adoption curve can occur due to other reasons even when there are no interactions, for example, when the probability distribution of individual characteristics within neighborhood exhibits discontinuities. In this case we would expect to see the presence of threshold effects due to exogenous characteristics $q_i = X_i$.

Given the hazard rate we can compute the adoption curve, $r(t|X_i, Y_{n(i)}, \pi^e_{n(i)})$

$$r(t|X_i, Y_{n(i)}, \pi^e_{n(i)}) = 1 - exp\left(-\int_0^t \psi(s|X_i, Y_{n(i)}, \pi^e_{n(i)}ds)\right) \tag{5}$$

and test for the presence of threshold effects. In particular, we test the null hypothesis that $H_0 : r_1 = r_2$, where

$$r_1(t|X_i, Y_{n(i)}, \pi^e_{n(i)}) = 1 - exp\left(-\int_0^t \psi_1(s|X_i, Y_{n(i)}, \pi^e_{n(i)}ds)\right),\ q_i < \lambda \tag{6}$$

$$r_2(t|X_i, Y_{n(i)}, \pi^e_{n(i)}) = 1 - exp\left(-\int_0^t \psi_2(s|X_i, Y_{n(i)}, \pi^e_{n(i)}ds)\right),\ q_i > \lambda \tag{7}$$

A second prediction of theory is pattern reversal. In our context, a pattern reversal occurs if the firms in the lower regime are adopting more rapidly than those in the another, whereas the private incentives experienced by members of each group predict the opposite pattern. In doing so, we introduce unobserved heterogeneity by adding a frailty parameter to the above models to account for the possibility of unobserved risk factors shared by firms within neighborhoods.

- *to be completed* -

4.2.1 Results

- *to be completed* -

5 Conclusion

- *To be completed* -

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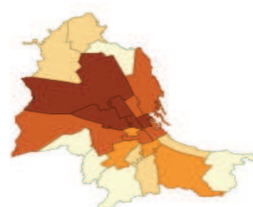
Figure 1: Firms in Palermo

(a) Location of firms in Palermo by zip code in 2005



(b) Percentage of firms that joined in each zip code by 2013

Table 1: Description and sources for the main variables used in the empirical analysis

Variable	Description	Source
Expected fraction of adopters in a zip code	Frequency of AP-firms in firm i's ZIP	AP
Expected fraction of adopters in a district	Frequency of AP-firms in the firm's i district	AP
Personnel costs	Labor Costs of firm i	CERVED
Total Assets	Tangible and intangible assets of firm i	CERVED
Bank loans	Total bank loans of firm i	CERVED
Firm's age	Age of legal constitution of the firm[13]	CERVED
Average age of firms in a zip	Age of firms within firm i's ZIP	CERVED
Within-ZIP firm's personnel costs	Average labor costs of firms within firm i's ZIP	CERVED

Table 2: Descriptive statistics

This table shows the descriptive statistics of the variables used in the empirical analysis. Averages and standard deviations are calculated on the available observations (not on individual firms)

	AP			Control		
	obs.	mean	std.dev	obs.	mean	std.dev
Expected fraction of adopters in a zip code	1107	0.0020	0.0024	2729	0.0015	0.0018
Expected fraction of adopters in a district	1107	0.0022	0.0024	2729	0.0016	0.0018
Personnel costs	1513	651743	2146099	3689	180910	601110
Total assets	1513	1321859	7222008	3678	844559	3824878
Bank loans	1353	811211	3991834	3120	659804	3309551
Age	1513	18jul1994	4898 (days)	3689	16apr1994	4542 (days)
Average age in a zip	1513	1aug1994	1142 (days)	3689	10apr1994	1053 (days)
Average personnel costs in a zip	1513	404772	588096	3689	282202	232271

Table 3: Hazards regressions

This table presents results for the hazards regression model in equation (4) using panel data. Standard errors in parenthesis. ***,**,* denote significant coefficients at 1%, 5% and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expected fraction of adopters in a zip code	1.034***	1.232***	0.834***		0.976***	0.931***	0.936***	1.024***	
	(0.215)	(0.451)	(0.067)		(0.217)	(0.267)	(0.458)	(0.304)	
Expected fraction of adopters in a district				1.740***					1.701***
				(0.270)					(0.331)
Personnel costs					0.221**	0.313**	0.316**	0.353**	0.231*
					(0.097)	(0.137)	(0.142)	(0.146)	(0.130)
Total assets					-0.049	-0.025	-0.025	-0.015	
					(0.031)	(0.036)	(0.036)	(0.036)	
Age					0.006**	0.004*	0.004*	0.005**	0.004
					(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Bank loans						-0.127	-0.146	-0.130	-0.085
						(0.087)	(0.093)	(0.090)	(0.079)
Average age in a zip code								0.000	0.007
								(0.013)	(0.013)
Average personnel costs in a zip code								-0.878	-1.212*
								(0.643)	(0.641)
Average revenues in a zip code								0.131*	0.166**
								(0.070)	(0.071)
Subjects	622	622	-	622	621	590	590	590	590
Obs	3199	3199	3837	3199	3194	2816	2816	2816	2816
Failures	127	127	-	127	127	119	119	119	119
Zip dummies	N	Y	N	N	N	N	Y	N	N
Frailty discrete	N	N	Y	N	N	N	N	N	N
LR χ^2	14.46	35.26	-	33.28	24.56	24.87	48.19	28.20	42.82
Prob	0.00	0.03	-	0.00	0.00	0.00	0.05	0.00	0.00

Table 4: Cox proportional hazards regressions

This table presents results for the Cox-PH duration model using cross-section data. Standard errors in parenthesis. ***,**,* denote significant coefficients at 1%, 5% and 10%.

	(1)	(2)	(3)	(4)
Expected fraction of adopters in a zip code	5.204***	2.584**	2.567**	2.963**
	(0.829)	(1.092)	(1.089)	(1.282)
Personnel costs		0.497***	0.403***	0.485***
		(0.159)	(0.128)	(0.148)
Total assets		-0.128**	-0.038	-0.052
		(0.152)	(0.056)	(0.059)
Age		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Bank loans			-0.236***	-0.240**
			(0.090)	(0.097)
Revenues			0.051***	0.041*
			(0.019)	(0.023)
Average age in a zip code				0.031***
				(0.009)
Average personnel costs in a zip code				-0.577
				(0.667)
Average revenues in a zip code				0.101
				(0.081)
Subjects	1266	711	679	679
Obs	1266	711	679	679
Failures	288	178	172	172
LR χ^2	38.33	20.38	26.69	38.00
Prob	0.00	0.00	0.00	0.00