CSEF
Centre for Studies in Economics and Finance

WORKING PAPER NO. 422

The Shadow Economy and Banks' Lending Technology

Salvatore Capasso, Stefano Monferrà and Gabriele Sampagnaro

December 2015

University of Naples Federico II | University of Salerno | Bocconi University, Milan

CSEF - Centre for Studies in Economics and Finance
DEPARTMENT OF ECONOMICS – UNIVERSITY OF NAPLES
80126 NAPLES - ITALY
Tel. and fax +39 081 675372 – e-mail: csef@unisa.it

WORKING PAPER NO. 422

The Shadow Economy and Banks' Lending Technology

Salvatore Capasso[*], Stefano Monferrà[**] and Gabriele Sampagnaro[**]

Abstract
Is there a relationship between bank monitoring models and the level of shadow economy? This paper develops a model of optimal lending technology to study the relationship between local underground economic activity and banks' lending choices. In turn, as the aggregate level of informality and tax evasion increase, it becomes more profitable for banks to screen and supervise borrowers using more costly in-depth monitoring technologies. A large dataset of regional Italian data confirms these conjectures.

JEL classification: G21, H26

Keywords: Shadow economy, lending technology, monitoring

Acknowledgements: An earlier version of this paper circulated under the title ''The underground economy and banks' monitoring model". We thank participants at the 2014 Conference of the Financial Engineering and Banking Society (University of Surrey) and at the workshop "Rethinking Finance for Stability and Growth", Mexico City, June 2014. We are particularly grateful to the participants of the 52th annual meeting of SIEcon (Trento) and to Gregory F. Udell for their valuable comments. All remaining errors are ours.

[*] ISSM, CNR and CSEF. Corresponding author: CNR-ISSM via Guglielmo Sanfelice, 8, 80134 Naples Italy; email capasso@issm.cnr.it

[**] Università di Napoli "Parthenope".

Table of contents

1. Introduction

The shadow economy[1] accounts for a sizeable proportion of employment and output in many countries such that its containment and control currently represent a major challenge for policy makers. In fact, by distorting incentives, undermining investment and reducing capital productivity, high levels of the underground economy can be very harmful to economic growth. Yet to confront the challenge and design efficient policies first requires understanding the nature of informality and its roots.

The choice between formality and informality can be fully understood only by comparing the associated costs and benefits. The benefits of informality – and the parallel costs of formality – are quite evident. Being informal implies lower costs in terms of tax payments and legal and regulatory compliance. Moreover, informality does not involves entry costs (Djankov et. al, 2002). Yet, being informal involves costs that go well beyond possible penalties and fines. Indeed, informal agents have limited or no access to public goods and services and face generally higher costs to access credit. These latter arise because by hiding income and activities, informal firms are less able to signal their profitability, and hence they encounter a higher probability of being credit rationed unless they meet more stringent credit conditions. For this reason, credit market conditions represent a relevant opportunity cost for those firms that choose informality. This relationship also implies that as financial markets develop and credit market conditions ameliorate, one should observe a lower level of aggregate informality in the economy.

However, the relationship between the credit market and the informal sector has rarely been investigated in either the theoretical or the empirical economic literature. Particularly, there exists scant literature addressing the link between the underground economy and financial development. Further, to the best of our knowledge, the mechanism through which the underground economy interacts with some aspects of the bank-lending process, such as monitoring and bank-firm relationships, has never been explored.

This paper tries to fill this gap and examines the relationship between banks' lending technologies and the level of the shadow economy from both a theoretical and an empirical point of view.

In granting credit, banks apply different lending technologies. The choice of technology is determined by a combination of various elements such as the primary information source, screening and underwriting policies and procedures, the loan contract structure, and monitoring strategies and

[1] Henceforth, we will interchangeably use the terms shadow, informal, hidden or underground economy to designate all of those economic activities, and the income derived thereof, that circumvent or avoid government regulation or taxation.

mechanisms (Berger and Udell 2006). We argue that lending technologies can also be influenced by the level of shadow economy according to the following mechanism.

Entrepreneurs going underground hide revenues and fabricate their financial accounts primarily to escape the tax burden and social security contributions. Yet by doing so, they become more opaque to potential lenders, and their ability to signal income returns and endowments decreases. The result of this action is an increase in the probability of being credit rationed.

Indeed, financial accounts and tax statements are among the primary sources of information needed by banks to grant credit. These types of documentation represent a relatively inexpensive way to collect information on borrowers. In fact, these types of documents enable, among others, the easy collection of files and records signaling the borrowers' endowments and incomes (*hard information*), which represent the bulk of what the literature labels as "transaction lending technology" (Berger and Udell, 2006). On the wide spectrum of lending technologies[2], the latter could be conceived to be the most efficient because they allow standardized procedures by decreasing the intensity of monitoring and screening and, in turn, lending costs. However, transaction lending technologies may be optimally implemented only when the bank primarily faces transparent borrowers. In the opposite situation, if the bank operates in a market plagued by informal firms that can only provide poor quality hard information, standardized lending procedures might decrease the banks' revenue to the extent that they cannot be profitable. In fact, when facing a large number of underground opaque firms and more intense informational problems, banks may find it optimal to mitigate these informational frictions through more intense monitoring actions that will allow them to penetrate firm accounts and go beyond the story contained in financial accounts and tax statements. Specifically, more intense monitoring enables private information (namely *soft information*) to be gathered that allows the bank to inspect the volume of hidden business operations and, consequently, to measure the firm's real business and profitability.

From the borrowers' perspectives, a switch from standardized procedures to a more intense monitoring technology is not necessarily damaging. In fact, if on the one hand, this shift may lead to an increase in the cost of credit – higher loan interest rates or additional collateral requirements –on the other hand, it entails a lower probability of credit rationing. From a lender's perspective, deep monitoring procedures are certainly more costly, but they deliver more accurate information on borrowers. Hence, if the bank operates in an environment in which it is difficult to gather information because of the widespread level of informality, a banking model characterized by more

[2] Berger and Udell (2006) argue that there are a number of distinct transaction technologies used by financial institutions, including financial statement lending, small business credit scoring, asset-based lending, factoring, fixed-asset lending, and leasing.

stringent and in-depth monitoring can offer rewards with respect to other apparently less costly banking models.

We, therefore, predict a positive relationship between the level of the underground economy and the intensity of bank monitoring.

This paper presents both a theoretical model and an empirical test. The model attempts to show how the level of the underground economy can affect a bank's optimal decision regarding the level of monitoring to apply. We formalize our idea in a simple theoretical framework in which banks optimally choose the lending technology in the presence of informal firms. Banks can either issue credit by employing low cost monitoring procedures (transaction lending technology) or by employing more in-depth investigations into borrowers' creditworthiness (relationship lending technology). Although the former technology is less costly, it is not optimal for use when a bank faces a large number of underground firms. Indeed, as the number of underground firms increases, the level of credit constrained firms increases as well, unless banks compensate for the opacity of informal borrowers through more intense monitoring – for example, by collecting more costly soft information. In other words, to maximize profits, banks trade off the increase in the cost of monitoring with an increase in the volume of credit issued. Therefore, the model predicts that given each technology's monitoring costs, the banks will more intensively use relationship lending instead of transaction lending as the number of informal firms grow.

By using data on a large Italian banking group, we empirically test the model predictions by means of a quantile regression, and the findings appear to confirm those predictions. In particular, a set of interactions between the shadow economy and the monitoring indicators show that high levels of informality are associated with a more intense use of bank monitoring.

However, the greatest challenge in the empirical strategy is the selection of a variable to measure both the shadow economy and bank monitoring efforts. For both variables, we were required to use proxies. More specifically, we use two alternative measures for the underground economy that are already employed in the literature: *i*) the share of irregular workers in total employment and *ii*) the fraction of income received in cash by individuals.[3] We attempt to capture bank monitoring effort through a set of three variables, each related to the bank-firm relationship (i.e., internal ratings, length of relationship, number of lenders).

We believe that we contribute to the existing literature on the shadow economy and financial intermediation in a few different ways. While other studies focus on the interaction between informality and financial development at a country level, to the best of our knowledge, this is the first study that attempts to describe the interaction between the shadow economy and bank behavior

[3] See Djankov *et al*. (2002), Loayza *et al*. (2005) and La Porta and Shleifer (2008)

in lending decisions from both a theoretical and an empirical point of view. In addition, while our empirical results are not directly comparable with others because of the pioneering character of this study, we believe that we add new insights into the selection of lending technology through our use of a detailed data set of approximately 30,000 bank-firm relationships. We also believe that the results are particularly significant because we focus on one country, Italy, which presents an ideal subject for analysis for several reasons. In particular, because the average level of the shadow economy is high and varies among the provinces, Italy is an ideal testing ground for observing the range of behaviors for a single bank operating in all provinces and, consequently, interacting with different levels of informality.

This paper has the following structure. Section 2 contains a brief description of bank monitoring technology. Section 3 contains a simple theoretical model that we empirically test in section 4. We draw some conclusions in section 5.

2. Related Literature

A novel feature of our analysis is that it allows us to elucidate the influence of the hidden economy on the loan monitoring process. In doing so, the paper ties together two strands of the literature that to date have remained separate. On the one hand, this paper is related to a recent strand of studies on the shadow economy that examine its link to financial development (Straub, 2005; Antunes and Cavalcanti, 2007, Blackburn *et al*., 2012, among others). On the other hand, this paper is related to traditional studies on the role of lending technologies paying particular attention to the collection of soft information (Petersen and Rajan, 1994; Berger and Udell, 1995; Boot, 2000; Berger and Udell, 2006). While the primary focus of this paper, i.e., the relationship between the shadow economy and the bank's choice of lending technology and monitoring effort, has never been explored, a scant literature has examined the interaction between the shadow economy and financial development.

By considering the tradeoff between the "entry costs" incurred by firms to operate formally and the benefits accruing from the use of key public goods, Straub (2005) analyses firms' optimal selection between formality and informality. Among other factors, the author shows that this choice is shaped by the working of credit markets and by the level of financial development because these influence the opportunity cost of accessing investment and participating in the formal market. Along a similar line of argument, Antunes and Cavalcanti (2007) measure credit market imperfections using the cost of enforcing financial contracts and suggest that these costs (regulation costs) are important in explaining the size of the shadow economy. More recently, Blackburn *et al.* (2012) develop a model of tax evasion and financial intermediation in which individuals may choose to conceal their true wealth status for the purpose of tax evasion. The amount of wealth disclosure and the collateral offered to secure a loan affects the terms and conditions of the financial contract made available to individuals. Hence, financial development negatively affects the level of the underground economy because it reduces the cost of credit and pushes firms to disclose more collateral. Further, the existence of a negative relationship between the level of underground economy and financial development has also been proved from an empirical point of view (Bose et. al, 2012; Capasso and Jappelli 2013; Dabla-Norris and Feltenstein 2005; Straub 2005).

The literature on lending technologies and the corresponding monitoring strategies is more abundant and well rooted in time.

The theory of financial intermediation argues that banks are different from other intermediaries because they function as delegated monitors that screen prospective borrowers, gather proprietary information, and develop close relationships with borrowers to mitigate informational asymmetries and incentives towards moral hazard (Diamond 1984; Ramakrishnan and Thakor 1984; Sharpe 1990). A tied relationship between lender and borrower can mitigate information asymmetries and facilitate access to credit.

A bank's optimal lending strategy is the result of a careful comparison between the costs and benefits involved in monitoring. These costs and benefits have been extensively analyzed in the literature.

Aside from producing information, monitoring can introduce the right incentives for firm management; agency problems, for example, can be reduced through a long term bank relationship including the threat of denying access to additional credit or reducing the amount of current loans (Rajan 1992). In addition, Von Thadden (1995) shows that a debt contract with periodic monitoring improves the efficiency of investment. Long-lasting collected information – i.e., usable for lending decisions over multiple periods – that is not easily reproducible by other financial institutions produces benefits for both lenders and borrowers. Indeed, borrowers with a close and repeated relationship with lenders have greater credit availability and a lower cost of capital than other borrowers (Diamond 1984, 1991; Haubrich 1989). Monitored financing allows firms to hold information confidential because they are not subject to the disclosure rules typical of arm's length financing. This argument suggests that a closer relationship with the lender will be associated with the collection of different types of information that serve to better monitor borrowers' financial conditions.

The nature and intensity of monitoring is influenced by the type of information to be collected. The literature identifies soft information as being a type that strongly characterizes relationship lending. A not-exhaustive definition identifies soft information as information that cannot be directly verified other than by the agent who produces it; it is not easy to summarize in a numeric code and is difficult to communicate in a verifiable manner even within an organization (Petersen and Rajan 1994; Stein 2002). This type of information plays a strategic role when the size of the borrower is smaller. Indeed, for small firms, relationship lending can be considered to be the most appropriate lending technique (Boot *et al.*, 2006). A well-established literature on relationship lending considers the collection of soft information, more than other types, to be a beneficial mechanism for producing information for both lenders and borrowers (Agarwal and Hauswald 2010; Berger and Udell 1995; Cole 1998; Degryse and Van Cayseele 2000; Elsas and Krahnen 1998; Petersen and Rajan 1994).

Yet monitoring is costly, and the cost depends on factors such as the duration of the relationship, the nature of the credit provided, the number of lenders involved, etc. In general, the higher the frequency and intensity of loan reviews (i.e., monitoring) are, the higher the cost (in absolute terms). However, borrowers with enduring relationships may require lower and decreasing monitoring costs (per unit of loan) because, after the initial interactions, they can subsequently be monitored less frequently (Blackwell and Winters 1997). In fact, Petersen and Rajan (1994) document that loan rates decline with longer relationships, while they increase with the number of lenders from which firms borrow. From a theoretical point of view, a long-term relationship with a lender allows the borrower to accumulate reputation, while moral hazard declines. Under these circumstances, the monitoring costs as reflected in loan interest rates diminish commensurately (Diamond 1984, 1989).

Monitoring costs also depend on the number of lenders involved with the same borrower. A large portion of the literature on the role of banks as information producers predicts a positive correlation between monitoring incentives and credit concentration. In particular, the existence of multiple bank lenders can deter the bank from monitoring the borrower for at least two reasons: 1) because monitoring is privately costly and banks do not coordinate in their choices, multiple-bank lending entails free-riding and duplication of effort (Diamond, 1984); and further, 2) the quantity and quality of the information extractable by each bank is decreasing in the number of relationships between the borrower and other lenders (Mester, *et al.*, 2007). On the contrary, delegating the task of monitoring to a single bank reduces information asymmetries, and a decreased ex post probability of default should follow.

Institutional factors affect the relative profitability of using the different lending technologies and thereby may also strongly influence the bank's optimal strategy and the intensity of monitoring. For example, a country's legal system can affect the ability of banks to employ specific contractual features, such as maturity, collateral, and covenants aiming at improving borrowers' information disclosure and hence decisions on credit issue (Berkowitz and White 2004; Sharpe, 1990). Analogously, the regulatory environment may influence credit by restricting access to the market to some intermediary or financial institutions.

We link the choice of bank lending technology to a specific institutional factor, the level of informal activity in the economy, which to the best of our knowledge has been neglected in the literature.

3. A simple model of credit issue with informal markets

Let us assume an economy populated by a large number of firms and a finite number of banks. Each bank has a monopoly for a specific region, which is populated by the same number of firms. Firms are endowed with an initial level of capital, A_i, which is uniformly distributed on $[0,1]$, implying that each firm in each region is uniquely identifiable by the level of capital endowment. Firms are also endowed with two investment projects: a high-tech project (H-T) and a low-tech project (L-T). We will assume that the high-tech project requires a high initial capital outlay, $I > 1$. Given the initial capital endowment, no entrepreneur can finance the project without accessing credit, i.e., $I - A_i > 0 \ \forall A_i \in [0,1]$. The return on the project depends on the entrepreneur's effort. Following the initial capital outlay, I, at time t, the project will deliver R units of output next period with probability p_s and e 0 units of output with probability $1 - p_s$, where $s = H, L$ denotes a high level of effort, H, or a low level of effort, L. By supplying a low level of effort, the entrepreneur obtains a private non-contractible benefit, $B>0$. Following Holmstrom and Tirole (1997), we assume that project H-T has a positive expected value only if the entrepreneur exerts a high level of effort:

$$p_H R - \gamma I > 0 > p_L R + B - \gamma I \tag{0}$$

The low-tech project, L-T, does not require a minimum level of capital. There are positive externalities from running this project in conjunction with the H-T project. By investing A_i at time t, the L-T project will deliver at time $t+1$ ΦA_i units of output if it runs jointly with the H-T project and ϕA_i if runs on its own, where $\Phi>\phi$.

We assume that entrepreneurs can hide their income and evade taxes only if they do not access credit. If entrepreneurs ask for a bank loan, they become immediately visible to the government and need to pay taxes on all of their income. This assumption implies that only entrepreneurs who run the L-T projects can hide and operate underground.

3.1 The Optimal Financial Contract

We now determine the optimal financial contract. Each entrepreneur undertaking the H-T project will ask for a minimum loan of $I - A_i$. The bank decides whether to grant the loan and determines the interest rate. The financial contract entails three elements: the loan size, the interest rate and the probability of credit rationing. Given equation (0), the bank monitors to force each entrepreneur to exert effort *H*. We assume that banks can apply two monitoring models (lending technologies): a model in which the bank employs standardized procedures to monitor and extract information (hard information) on the firm's profitability and a model in which the bank very closely monitors the firm and uses all available channels to investigate the business and detect firm profitability (soft information). Recalling the standard terminology, we will refer to the first as a "transaction lending model". This model entails lower monitoring costs per loan but is less efficient at detecting non-profitable loans and at reducing the risk of moral hazard. We will refer to the second model as a "relationship lending model". This model entails higher monitoring costs but involves more efficiency in loan screening and in reducing moral hazard. Obviously, these banking models lead to two different financial contracts. We can label the financial contract that emerges when the bank applies the transaction lending model as the "standard contract" (SC), while we can define the "monitoring contract" (MC) as the financial contract emerging when the bank applies the relationship lending model.

The most profitable banking model for the intermediary is determined by comparing the models' net expected profits. It is interesting to anticipate that because the number of firms going underground can affect the bank's expected revenues and costs, the level of the underground economy can ultimately determine the optimal lending technology. We now turn to determine the bank's expected profit.

The SC contract

We assume that both the bank and the entrepreneur are risk neutral. At time *t*, the firm asks for a loan size $I - A_i$ and invests *I* in project H-T. Next period, at t+1, if the project fails, no one receives any payment, and if the project succeeds, the entrepreneur obtains $R_f > 0$ and the intermediary obtains $R_b > 0$, where $R_f + R_b = R$. The contract must be such that the entrepreneur has the incentive to strictly prefer effort *H* over *L*. The incentive compatibility constraint is

$$p_H R_f \geq p_L R_f + B \iff R_f \geq \frac{B}{p_H - p_L} \qquad (0)$$

Because the bank extracts all of the surplus (it has monopoly power), the firm's repayment, R_f, is set to the minimum:

$$R_f = \frac{B}{p_H - p_L}. \tag{0}$$

The bank's repayment is

$$R_b = R - R_f = R - \frac{B}{p_H - p_L}. \tag{0}$$

By assuming that banks have an opportunity cost for their funding *γ*, the bank will grant credit only if

$$p_H\left(R - \frac{B}{p_H - p_L}\right) \geq \gamma(I - A_i) \tag{0}$$

Recalling that the initial level of capital is uniformly distributed on [0,1], constraint (0) implicitly defines the minimum level of capital below which firms are credit rationed:

$$\underline{\hat{A}}(\gamma, B, R) = I - \frac{p_H}{\gamma}\left(R - \frac{B}{p_H - p_L}\right). \tag{0}$$

In other words, only firms with a sufficient level of initial capital endowment $A_i \geq \underline{\hat{A}}$ will be able to obtain a loan to run the H-T project. Firms with an initial level of capital endowment $A_i < \underline{\hat{A}}$ will be credit rationed. $A_i \in [0,1]$; $\underline{\hat{A}}$ is the share of credit constraint firms, and $1 - \underline{\hat{A}}$ is the share of firms undertaking the H-T project.

The MC contract

Under more stringent monitoring activity, it is more difficult for borrowers to deviate from behaving optimally for the bank. We formally introduce this case by assuming that in the high intensity monitoring model (relationship lending), the private benefit to entrepreneurs from supplying low effort, *L*, is reduced to $b < B$. Yet, to issue a loan requiring a higher level of monitoring, the bank sustains a cost *C* that is higher than the cost associated with issuing a loan with an SC contract.[4] Hence, under this contract, the entrepreneur obtains

$$R_f = \frac{b}{p_H - p_L}, \tag{0}$$

while the bank's repayment is

[4] To simplify, we assume that the monitoring cost associated with a loan based on the SC contract is zero.

$$R_b = R - R_b = R - \frac{b}{p_H - p_L}. \tag{0}$$

The bank's participation constraint is

$$p_H\left(R - \frac{b}{p_H - p_L}\right) - C \geq \gamma(I - A_i). \tag{0}$$

Hence, the minimum level of capital below which we have credit rationing under a high intensity monitoring model is

$$\underline{\tilde{A}}(\gamma, b, R, C) = I + \frac{C}{\gamma} - \frac{p_H}{\gamma}\left(R - \frac{b}{p_H - p_L}\right). \tag{0}$$

Therefore, firms with an initial level of capital endowment $A_i \geq \underline{\tilde{A}}$ will obtain credit and run the H-T project. Firms with insufficient initial resources, i.e., $A_i < \underline{\tilde{A}}$, will be credit constrained and will only run the L-T project.

3.2 The firms' optimal choice

Once the bank has defined all components of the financial contract, interest rates and credit rationing, the firm chooses which investment project to undertake, H-T and/or L-T, and the amount of resources to invest in each project. By choosing the amount of investment in each project, firms implicitly choose the loan size. Indeed, project H-T requires an initial capital outlay *I*, which each firm can self finance up to $A_i \geq \underline{\hat{A}}$ if it is offered an SC contract or $A_i \geq \underline{\tilde{A}}$ if it is offered an MC contract. Because the repayment is given and does not depend on the loan size (see eq. (0) and eq. (0)), each firm will find it optimal to maximize the loan size by borrowing $I - \underline{\hat{A}}$ if it is offered an SC contract and $I - \underline{\tilde{A}}$ if it is offered an MC contract. The remaining resources will be invested in the L-T project.

This logic implies that firm *i*'s expected utility under a standardized model of intermediation is

$$(1-\tau)[p_H R_d + \Phi(A_i - \underline{\hat{A}})] = (1-\tau)[p_H \frac{B}{p_H - p_L} + \Phi(A_i - \underline{\hat{A}})] \tag{0}$$

while firm *i*'s expected utility under a high intensity monitoring model of intermediation is

$$(1-\tau)[p_H R_d] + \Phi(A_i - \underline{\tilde{A}}) = (1-\tau)[p_H \frac{b}{p_H - p_L} + \Phi(A_i - \underline{\tilde{A}})]. \tag{0}$$

Credit rationed firms will instead invest in the L-T project and obtain ϕA_i. However, these firms can avoid taxation by hiding their income from the government.

3.3 The banks' optimal choice

The optimal intermediation model can be determined by comparing the expected net profits under the two alternatives. Applying standardized procedures involves costs that are decreasing in the volume of credit issued. Hence, let us assume that *K* represents the resources (cost) required to establish the standardized procedure. The expected profit of a bank issuing the SC financial contract is

$$\Pi_{SC} = (1-\underline{\hat{A}})p_H R_l - K = (1-\underline{\hat{A}})p_H\left(R-\frac{B}{p_H-p_L}\right)-K\ . \tag{0}$$

Given that under relationship lending, only $1-\underline{\tilde{A}}$ firms access credit and recalling that the intermediary sustains a per loan monitoring cost, *C*, the expected profit is

$$\Pi_{MC} = (1-\underline{\tilde{A}})\left(p_H R_l - C\right) = (1-\underline{\tilde{A}})\left[p_H\left(R-\frac{b}{p_H-p_L}\right)-C\right] \tag{0}$$

The bank prefers the SC over the MC contract if

$$(1-\underline{\hat{A}})p_H\left(R-\frac{B}{p_H-p_L}\right)-K \geq (1-\underline{\tilde{A}})\left[p_H\left(R-\frac{b}{p_H-p_L}\right)-C\right] \tag{0}$$

We can solve bank's problem in the following way. By combining (0) and (0), we obtain

$$\underline{\tilde{A}} = \underline{\hat{A}} + \frac{C}{\gamma} - \frac{p_H}{\gamma}\frac{B-b}{p_H-p_L} \tag{0}$$

The latter expresses the level of credit rationed firms in the relationship model in terms of credit rationed firms in the transaction model. Equivalently, because the firms that do not access credit go underground, equation (0) links the levels of the underground economy under the two intermediation regimes. By using (0), one can rewrite equation (0) as follows:

$$\Pi_{MC} = \left[p_H\left(R-\frac{b}{p_H-p_L}\right)-C\right]\left(1-\frac{C}{\gamma}+\frac{p_H}{\gamma}\frac{B-b}{p_H-p_L}\right)-\left[p_H\left(R-\frac{b}{p_H-p_L}\right)-C\right]\underline{\hat{A}} \tag{0}$$

The latter and equation (0) show that bank profits are always decreasing in the underground level ($\underline{\hat{A}}$). Assume that when *K*=0, the intermediary obtains a higher net return on each loan under the SC contract (the slope of Π_{SC} is greater than the slope of Π_{MC}), i.e.,

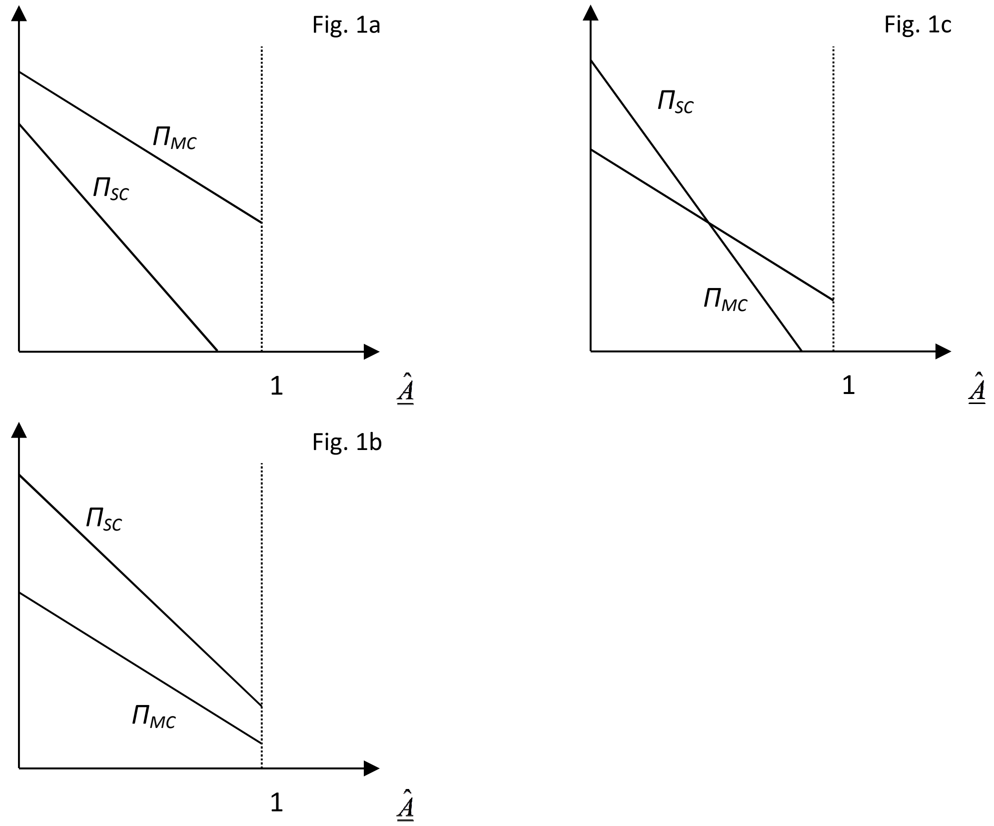
$$C > p_H\frac{B-b}{p_H-p_L}\ , \tag{0}$$

Then, we have three possible scenarios depending on the size of the underground economy:

Case 1: contract MC always dominates contract SC (Fig. 1a)

Case 2: contract SC always dominates contract MC (Fig. 1b)

Case 3: contract SC dominates MC for low levels of the underground economy (Fig. 1c)



We now very briefly discuss each case in turn and the conditions under which each of the above regimes can emerge. By comparing expected payoffs, one can easily find that the MC contract always dominates the SC contract (Fig. 1a) if

$$K > \left[C - p_H \frac{B-b}{p_H - p_L} \right] + \Lambda , \tag{0}$$

where $\Lambda = \left[p_H \left(R - \frac{b}{p_H - p_L} \right) - C \right] \left(\frac{C}{\gamma} - \frac{p_H}{\gamma} \frac{B-b}{p_H - p_L} \right)$. Recalling that expected profits are decreasing in $\underline{\hat{A}}$ and that the slope of Π_{SC} is greater than the slope of Π_{MC}, SC always dominates (Fig. 1b) if for $\underline{\hat{A}} = 1$,

$$K < \Lambda . \tag{0}$$

Case 3 emerges (Fig. 1c) if

$$\left[C - p_H \frac{B-b}{p_H - p_L} \right] + \Lambda > K > \Lambda \tag{0}$$

In other words, given all other parameters, if the costs to implement standardized procedures are not too high or too low, the optimal lending regime depends on the level of the underground economy. For a low level of the underground economy (low values of $\underline{\hat{A}}$), the SC dominates. The opposite occurs for high levels of the underground economy[5]. In this is the case, then a threshold level of underground economy exists above which the monitoring contract dominates the standard contract. One can define this threshold level of the underground economy as follows:

$$\underline{\hat{A}}^{*} : \Pi_{SC}(\underline{\hat{A}}) = \Pi_{SC}(\underline{\hat{A}})$$

In other words, for reasonable values for the monitoring and standardization costs, the optimal lending technology is jointly determined with the level of underground economy. High levels for the informal economy involve the more intense use of monitoring and the prevalence of the relationship lending model.

4. Empirical evidence

4.1 Measuring the impact of the shadow economy on bank monitoring

Banks employ many rules to evaluate firms' credit worthiness, and many of these are related to the gap between bank borrowing and the size of the firm's business. Among these rules, one of the rules of thumb employed by banks is an analysis of the ratio between bank debt and the borrower's turnover, which can be represented as follows:

$$\text{Debt to Sales Ratio}_{\text{ij}} = \frac{\text{DEBT}_{\text{ij}}}{\text{SALES}_{\text{i}}}$$

where DEBT is the credit granted to firm *i* by bank *j*, which is monitoring loans[6].

A common wisdom among bankers is that a high value for the above ratio alerts the bank that the borrower's credit quality is deteriorating. Though there is no common threshold value for the

[5] The level of the underground economy is jointly determined with the optimal financial contract. Given the exogenous parameter values, I, p_H, p_H, γ, R, B, b, the financial contract determines the threshold level of collateral necessary to access credit $\underline{\tilde{A}}$ or $\underline{\hat{A}}$. The level of credit rationing is determined, as is the level of underground economy. Given the level of underground economy, the overall bank profits are determined. Banks optimally choose the monitoring technology and in so doing, implicitly determine the level of underground economy.

[6] This debt should not be confused with the total amount of debt that firm *i* holds with all of its lenders.

ratio, a general rule is that a ratio greater than one indicates a critical situation that requires urgent action by the bank (including ending the relationship)[7].

We observe this ratio to extract a relationship between monitoring intensity and the existence of fraudulent behavior by the firms as regards tax payments.

The basic concept is that if the ratio is higher than normal and the bank continues to lend to the borrower, then it is likely that the latter is hiding revenues (i.e., sales are undervalued, and consequently, the *Debt_to_Sales* ratio is overvalued). The most likely explanation for bank behavior in this case (as it continues to lend to the borrower) is that the bank might be aware of the existence of informal behavior in terms of hidden revenues. A bank may reach this conclusion if it has intensively monitored the firm and gathered private information that reveals the volume of hidden business.

Therefore, it is presumable that banks operating in geographical areas and industrial sectors with a more concentrated hidden economy may have incentives to intensively monitor those borrowers that are hiding revenues. As mentioned above, a tied relationship with a borrower involved in a shadow business should induce the bank to ignore the *Debt_to_Sales* ratio because it might be affected by a deliberate underestimation of the denominator.

4.2 Measuring banks' monitoring efforts

Despite being a fundamental operating function, it is not easy to observe and measure banks' monitoring activity. Monitoring is not related to an individual clearly identifiable variable but is the counterpart of many different operations. The difficulty of capturing monitoring through a single variable is well known in the literature.

Blackwell and Winters (1997) examine the effect of monitoring and banking relationships on loan interest rates. To measure bank monitoring, they use a loan classification that is based on credit risk. The basic concept behind this measure is that the amount of default risk positively affects the bank's monitoring; thus, riskier loans are more heavily monitored with respect to others. For example, after the issue of the loan, the borrower must provide a level of documentation that is certain to be more abundant and detailed than the documentation requested from a perceived less risky borrower.

A large body of literature posits that bank monitoring could depend on, and hence be detected by, the number of banking relationships. In the case of a single bank relationship, the bank might

[7] More precisely, the choice of Debt_to_Sales as a key variable of this study stems from interviews with bank managers rather than from the academic literature, which, as we know, rarely uses this variable although it may be very informative.

have higher incentives to monitor the firm (Diamond, 1984; Ramakrishnan and Thakor, 1984). In fact, as well argued by the literature on financial intermediation as developed by Diamond (1984) and others (see Gorton and Winton, 2003, for a review), the presence of more lenders can generate free riding problems. On the assumption that a higher concentration of creditors facilitates monitoring and screening, Ahn and Choi (2009) employ the number of lenders as a measure of the strength of bank monitoring. Credit concentration is also considered to be a key variable by Cai *et al*. (1999), who measure the level of bank monitoring by estimating the ratio of bank loans to total outstanding debt.

In line with the literature, in this study, we use the following three variables as proxies for the intensity of monitoring: *i*) the internal credit risk rating of the firm (Blackwell and Winters, 1997); *ii*) the number of lenders per firm as a measure of credit concentration, given that more lenders might be associated with a lower level of monitoring by each lender; and *iii)* the duration of the relationship between the bank and the firm because a long relationship may be associated with a higher number of contacts between the lender and the borrower.

4.3 Data

The following empirical analysis relies on data provided by an Italian bank group that is one of a handful of truly national banks operating in Italy. The bank group has one parent company and seven subsidiaries, lends to borrowers located in 106 out of 110 provinces and operates in 165 industries (six-digit NACE classification). We collected a credit file that contains information at firm level. For each firm, we have information on credit terms (such as amount of the loan, risk, collateral, duration of relationship, credit concentration), firm characteristics and other variables that control for the structure of the market in which the firm operates. After checking for inconsistencies and duplicates[8], our sample consists of 29,568 relationships between firm *i* (*i*=1…29,568) and one of the *j* (j=1…8) banks of the group collected at the end of 2008 (cross sectional data).

Because the database is provided by a single bank, we must take into account the sample selection issue. The credit policy of the bank, which depends on firm characteristics such as size and risk, is clearly endogenous. This policy may bias the results and prevent us from making generalizations.

[8] We have removed observations for firms that have relationships with more than one bank of the group because we need to exclude the possibility that the bank knows the clients indirectly (i.e., through information collected and transmitted by other subsidiaries).

However, the use of credit-file data rather than industry surveys enables us to focus the analysis on information that is directly related to actual credit decisions. In comparison to industry survey studies — which are conducted exclusively using data collected by the national credit register (specifically, these studies analyze the credit information for each firm within the entire banking system) — credit-file data have the unquestionable advantage of capturing the set of characteristics that are effectively used by the bank to make lending decisions.

4.4 Estimation procedure

To investigate the impact of the shadow economy on the choice of bank lending technology, we regress the *Debt_to_Sales* ratio (*Debt_to_Sales*) on a measure of the underground economy and a series of control variables. The full empirical model to be estimated is the following:

$$BANK\_to\_SALES = f\begin{pmatrix} \text{Shadow Economy,} \\ \text{Monitoring Variables,} \\ \text{Monitoring X Shadow Economy (interactions),} \\ \sum_m \beta_m Bank\_specific\ Variables \\ \sum_m \beta_m Firm\_specific\ Variables \end{pmatrix}$$

While the ideal form of estimation procedure would have a monitoring variable on the left side and include a measurement of shadow economy on the right side, our approach is different. Because it is hard to find a unique variable that is able to capture bank monitoring effort due to its multidimensional nature, we employ more than one right-side monitoring variable and measure the impact of the shadow economy through interaction terms.

In particular, remembering that our basic idea is 1) a high level of *Debt_to_Sales* may reveal that borrowers are hiding revenues that, if known, would improve borrower credit worthiness, and 2) the bank may be aware of this fraudulent behavior after collecting private information, we expect that a high *Debt_to_Sales* level is associated with high monitoring intensity and a shadow economy.

Because our objective is to test whether the underground economy and monitoring move according the above mentioned mechanism when the dependent variables assume very high levels, we apply a quantile regression, which we consider to be particularly appropriate for this investigation.

Quantile regression allows us to estimate the impact of the explanatory variable not only on the mean but also on different levels or quantiles of the distribution of the dependent variable (Koenker and Basset, 1978).

Summarizing the general form, suppose that Y, the outcome variable, and X are the explanatory variables, and let $F_{Y|X}^{-1}$ and $F_{Y|X}^{-1}(\tau)$ denote, respectively the conditional distribution function and the τ-quantile of Y given X; in this case, the conditional quantile model can be represented as follows:

$$F_{Y|X}^{-1}(\tau) = X'\beta_n(\tau)$$

The estimation of quantiles provides much more information about the distribution of Y when compared with mean regression estimators (OLS). In particular, the key point of the comparison with OLS is that quantile regression provides coefficient parameters that minimize the sum of the absolute residuals, whereas ordinary least squares minimizes the sum of squares. Therefore, quantile analysis is certainly more robust with regard to outliers (Koenker and Hallock 2001).

4.5 Variable description and expected signs

The descriptions and summary statistics of the dependent variable, *Debt_to_Sales*, and of the other variables are reported in Table 1.

About here Table 1

As a measure of the shadow economy, we employ the irregular job rate (IRR_JOB). This rate is the ratio between the irregular and regular labor force, and it is supposed to be positively related to the share of the shadow economy. Scholars have provided different alternative proxies for the underground economy based on different estimation approaches (the currency demand approach, the gap between effective and potential electricity consumption or the multiple indicators approach)[9], all of which are questionable and have weaknesses. The concept of measuring the underground economy through the job market is consistent with those studies that consider the intensity of regulations, primarily labor market regulations, as one of the most important incentives for staying out of the official economy (Friedman *et al.* 2000; Johnson *et al.* 1997; Johnson *et al.*

[9] See Djankov *et al*. (2002), Loayza *et al*. (2005) and La Porta and Shleifer (2008).

1998)[10]. The data on irregular labor are provided by the Italian National Institute of Statistics (ISTAT).

As we suspect that high levels for the *Debt_to_Sales* ratio can be explained by a false value for the denominator due to hidden revenues, we predict a positive correlation between IRR_JOB and the dependent variable.

Then, we consider different factors that might characterize bank lending technology. A first set of control variables is strictly related to the bank's monitoring activity. Because monitoring actions are difficult to observe directly, we attempt to approximate monitoring by means of three variables.

These variables are *i)* the length of the credit relationship (DURATION), *ii)* the number of lenders involved with the firm (BANKS) and *iii*) the risk attributed by the bank to the firm (RISK). It is useful to provide a few details about these variables.

DURATION measures the relationship between firm *i* (i=1…29,568) and bank *j* (j=1…8) using the (log) number of years. Repeated borrower-lender interactions may be consistent with a more intense use of monitoring. A long relationship offers multiple occasions for interaction and may reflect more intensive monitoring through the collection and evaluation of soft information. However, the frequency of contact can decrease in the length of the relationship because of the knowledge originated by information collected in the past.

A second variable that might affect monitoring is the exclusivity of the bank-firm relationship. The variable BANKS collects the (log) number of lending banks for each firm. Consistent with the free-riding approach (Diamond, 1984; Ramakrishnan and Thakor, 1984), we associate a high (low) value of BANKS with a low (high) intensity and frequency of monitoring actions. Hence, the expected sign of BANKS is negative.

RISK is an ordinal measure of borrower quality. It represents the internal borrower rating estimated by each bank *j*. The banks' internal ratings system provides 10 classes of risk (class 1 is the least risky, class 10 is the most risky)[11] plus one, the D class, that denotes firm default risk. We predict a positive sign on this variable in line with Blackwell and Winters (1997), who find a positive relationship between monitoring frequency and loan interest rates (i.e., risk).

We then add other control variables to account for the loan contract terms, market competition and firm-specific characteristics.

[10] Regarding the case of Italy, Gobbi and Zizza (2012) use the amount of irregular employment as a proxy for the informal economy and show a negative relationship between the latter and the lending volume.

[11] We normalize the number of internal rating classes to 10 to preserve the privacy disclaimer of the bank that has provided the data.

With this aim, we include in our analysis DISTANCE, which provides the (log) value for the distance between the province of the local operating branches that serve borrowers and the city in which the bank headquarters is located. Because soft information is difficult to code and to transmit formally from the local manager (who collected it) to the responsible upper organizational layer of the bank (e.g., loan approval team), we expect that branch managers with a low (high) value of DISTANCE have (do not have) an incentive to collect soft information (Stein, 2002, Berger *et al.* 2005). Then, considering the possible positive relationship between the amount of soft information and the tolerance of the borrower's fraudulent behavior by the bank, we expect a negative sign for DISTANCE.

The bank's market power is captured by DENSITY, which reports the number of local branches for the banks in our sample per 1,000 firms at province level[12].

It is plausible to presume that a high density of branches for bank *j* located in a certain province increases the likelihood that the borrowers of that area maintain a long-term relationship with the bank (due to proximity and the bank's leadership position in that market). For this reason, we expect this variable to be positively correlated with the amount of information about the firm. Hence, this variable may play a role in our specification to the extent that it controls for the knowledge accumulated by the bank about the local area and the local firms, including their compliance with fiscal rules. Thus, the expected sign of this variable is positive.

Firm size also appears to play a significant role in determining credit issue. The size of firms is captured by a categorical variable provided by the banks and is classified in four categories: very small, small, medium-sized and large.

Finally, we saturate the regressions with 13 (*n*-1) dummies for industry (where firms operate) and 7 (*n*-1) dummies to control for the banks of our sample.

4.6 Empirical Results

In this section, we analyze the regressions of the dependent variable (the ratio between the debt granted by the bank and the borrower's sales) on the level of the underground economy and a set of control variables.

About here Table 2

[12] Recalling that our sample consists of information on the relationship between bank *j* (where *j*=1…8) and firm *i* (where *i*=1…29,568), this variable is calculated as follows: $DENSITY_{ijk} = \left[\left(NumBranch_{ijk}\right)/\left(TotFirms_k\right)\right]\cdot 1000$, where $NumBranch_{ijk}$ is the number of bank branches of bank *j* established in province *k* (k=1...110) where firm *i* is located, while $TotFirms_k$ is the number of firms active in province *k.* Thus, *DENSITY* reports the number of local branches for the banks in our sample per 1,000 firms at the province level.

We predict that the levels of *Debt_to_Sales* might be affected by the amount of hidden income and revenues because high levels for the *Debt_to_Sales* ratio can be explained by underreported sales. To prove this prediction and to measure the impact of the shadow economy, we include IRR_JOB in each model to measure the impact of the shadow economy at a regional level. Hence, the expected sign is positive.

The results in Table 2 appear to confirm the key role of the shadow economy in determining our proxy of bank behavior. The estimated coefficients of IRR_JOB are positive and highly statistically significant only for the top quantiles. It is interesting to report, for example, that the magnitude of the coefficient increases from the 75th to the 90th percentile by more than 226%. We believe that these findings are truly in line with our expectations that high values of *Debt_to_Sales* reflect the hidden business of the firm, which is detected by the bank through more intense monitoring.

The basic concept behind the linkage between the dependent variable and the monitoring variables is the following. High levels of *Debt_to_Sales* can predict the firm's involvement in informal sectors. In this case, our theoretical model predicts that the bank lending to the firm has chosen to apply a MC characterized by highly intensive monitoring actions. Hence, the set of three monitoring variables should capture a positive correlation between monitoring actions and the higher quantile of *Debt_to_Sales* ratio because we believe that this part of the distribution could be explained by hidden sales.

We note that all three variables considered to be proxies of monitoring (DURATION, BANK and RISK) show the expected signs and are statistically significant at the 1% level. More interestingly, they increase monotonically across quantiles coherently with our concept that higher values of *Debt_to_Sales* are explained by hidden sales and the borrower's fraudulent behavior might be known to the bank through intense monitoring actions.

In particular, DURATION shows coefficients with a positive sign and is statistically significant at the 1% level. Because a long lasting relationship increases the number of contacts between bank and firm, we interpret this variable as a proxy of lender monitoring actions. Because we observe that the value of coefficients increases across the quantiles, we conclude that there is a positive linkage between monitoring and the tax avoidance practices pursued by borrowers. Yet the frequency of contacts could be not linear in the length of the relationship. While contacts are frequent at the beginning of the relationship, they decrease over time. To account for non-monotonicity in the effects of DURATION, we add the square of DURATION to our set of explanatory variables. As expected, this variable displays negative and significant coefficients.

BANKS appear to play a central role. The coefficients are negative and statistically significant at the 1% level, meaning that a decrease in the number of lenders (including the extreme case of one lender) increase the probability that *Debt_to_Sales* reaches higher values. Because the low number of lenders encourages the monitoring efforts of the bank, this result can be interpreted to be in line with our prediction of a positive association between monitoring intensity and the silent awareness and approval of the firm's tax avoidance by the bank. Further, we note that the coefficient of BANKS increases gradually when passing from low to high quantiles, offering plausible proof of our latter prediction.

The third variable that indicates intense monitoring efforts is RISK because monitoring efforts are more intense for riskier firms. In this case as well, the results are completely in line with expectation. The coefficient values are positive, statistically significant at the 1% level and with increasing values. This finding should be interpreted as further evidence for how the monitoring mechanism allows the bank to notice the borrower's hidden business and to tolerate a higher level of *Debt_to_Sales*. However, endogeneity concerns arise with this variable: we suspect a reverse causality between risk and the level of the *Debt_to_Sales* ratio because the latter indicates the level of firm debt. Due to the difficulty of finding an instrumental variable that can satisfy both the relevance condition and the exclusion restriction required by an IV approach, we run the baseline regression without RISK, and we note that the results remain unaltered[13]. Hence, while one of the three-monitoring variables could bias results, the other two variables (DURATION and BANKS) continue to support our prediction.

The covariate effects of the *Debt_to_Sales* ratio at different quantiles for the distribution are particularly illustrative as depicted in Figure 2. The latter plots distinct quantile regression estimates ranging from the 0.05 to the 0.95 percentiles as a solid curve with filled dots. The ordinary least squares estimate of the conditional mean effect is represented by the dashed line, while the two dotted lines represent the conventional 90% confidence intervals for the least squares estimate. The grey area represents a 90% pointwise confidence interval for the quantile regression estimates.

While we suspect that high values for the *Debt_to_Sales* ratio could be determined by the underreporting of the denominator (sales), we also need to take into account the existence of contract terms that explain high values for the numerator (debt). We therefore add COLLAT to determine the effect of loan collateralization on credit. The coefficients of this variable are positive and highly significant in all specifications, implying that the presence of collateral increases firms' credit availability. The result is consistent with the strand of literature that considers collateral to be a remedy to credit rationing due to its role as a screening device (Chan and Kanatas, 1985; Bester,

[13] We decided to omit the table of results for brevity; it is available upon request.

1987; Besanko and Thakor, 1987) and because it reduces the "adverse selection" problem (e.g., Boot *et al*. 1991, Boot and Thakor, 1994; Chen, 2006).

The impact of DISTANCE is negative and statistically significant at 1%. This variable also appears to play a central role in determining the dependent variable to the extent that a greater distance between the local branch (that gathered soft information about the borrowers) and the headquarters reduces the probability of a high *Debt_to_Sales* ratio at the firm level[14].

Finally, the concentration of bank branches around the province of firms (DENSITY) positively affects the *Debt_to_Sales* ratio except for values higher than the 90th percentile.

Overall, the above analysis shows a positive relationship between the probability that one firm pursues inappropriate tax behavior and the intensity of bank monitoring efforts, including when we control for bank contract terms, market characteristics and firm specific variables.

4.6.1. Interactions between monitoring and the shadow economy

Although previous results confirm a positive linkage between *Debt_to_Sales* and both monitoring intensity and the shadow economy, one needs to show more clearly that the impact of the shadow economy is manifested through a more intense use of monitoring and, implicitly, a shift in the use of lending technology towards relationship lending (the shift from the *SC* to the *MC* as discussed in the theoretical model in section 3). In the quantile regression, we therefore add three interaction terms between IRR_JOB (the shadow economy) and, one at a time, the three monitoring variables (respectively, DURATION, BANK and RISK).

We expect that the coefficient of each interaction term will show the same sign as the coefficient value of the monitoring variable previously estimated (Table 2). For example, regarding the interaction IRR_JOB * DURATION, we predict a positive sign in that an increase of duration in an area with a high value for IRR_JOB, increases the effect on *Debt_to_Sales* (especially for the higher quantiles of the distribution). This rationale induces us to predict a negative and positive sign, respectively, for the following interaction terms: IRR_JOB*BANK and IRR_JOB*RISK.

We therefore run three new quantile regressions, each with a different interaction term. The results are reported in Table 3; for brevity, we only report results for the top two quantiles (the 75th and 90th), as the other quantiles are uninteresting as regards our goal.

About here Table 3

[14] This finding is consistent with the part of the literature on banks' distance that argues that proximity to the bank can be beneficial for borrowers (e.g., Agarwal and Hauswald, 2010; DeYoung *et al*., 2008; Degryse and Ongena, 2005).

Unlike the baseline regression, the variable that captures the shadow economy is generally not statistically significant and shows an alternation of signs. However, we are not concerned with this finding because we believe that the effects of informality are now captured by the interaction term.

Model (1) in Table 3 shows that the interaction term (IRR_JOB * BANK) has a negative and 1% significant coefficient. Remarkably, the absolute value of the coefficient increases from the 70th to the 90th quantile. Interestingly, the coefficient of the interaction term has the opposite sign in the lower quantiles (not reported in the tables). This finding is consistent with our primary prediction and represents further support for the appropriateness of using quantile regression.

In model (2), we estimate the baseline regression by introducing IRR_JOB*DURATION. In this case, the sign of the interaction term for the top quantiles is positive and highly significant. This result signals that the positive effect of monitoring on the *Debt_to_Sales* ratio is more severe in regions with a high share of the underground economy. Not surprisingly, we observe that the absolute values of the coefficients increase monotonically from the lowest to the highest quantile.

Finally, to establish the role of monitoring when we consider RISK as the proxy variable, we add the third interaction, IRR_JOB*RISK. From the results presented in model (3), we observe that the coefficient is positive and significant at the 1% level for the 90^{th} quantile, confirming our basic prediction.

The above results confirm that the effects of the informal economy on the highest quantiles of the Debt_to_Sales ratio are associated with the stronger effects of monitoring. We interpret this result as a signal of a change in banks' lending technology (a switch to the Monitoring Contract in the theory section) in the presence of a large share of informal economy (measured by $\underline{\hat{A}}$ in the theory section).

4.6.1. Robustness check

Finally, we stress test our results using a different variable for the shadow economy. Specifically, as a measure of the underground economy, we employ the fraction of income received in cash by individuals (see Capasso and Jappelli, 2013). This indicator is based on the concept that informal activities give rise to cash transactions. The indicator is built on data drawn from the Bank of Italy's Survey of Household Income and Wealth, which contains a question of this type: *Last year, did you receive part of your (or your family) income in cash? what fraction?* The indicator is simply the ratio of income received in cash to total income (in 2006).

We run the baseline regression of *Debt_to_Sales* on the new variable, which we name CASH, respectively with and without interaction terms as in the previous section. The results are presented in Table 4 and Table 5.

About here Table 4

About here Table 5

Not surprisingly, the results are unchanged. We observe (without exception) that the sign of all variables holds with the same level of statistical significance. More interestingly, the coefficients display the same dynamic pattern when passing from lower to higher quantiles and are therefore truly consistent with the previous findings.

We believe that this result indicates that the linkage between informality and monitoring control is also robust to different measures of the shadow economy.

4.6.2. Caveat Emptor

However, although our results elucidate a phenomenon not previously considered, some caveats need to be mentioned. The first caveat regards the value of our measure of monitoring. While we believe that the three variables measure monitoring effort, we must admit that they do not represent a pure measure of monitoring effort, at least from a theoretical point of view. The ideal method for measuring the monitoring actions of a bank is to count the number of hours (at the month, quarter or year level) and/or the quantity and quality of personnel employed by the bank to monitor its customers. However, we believe that the lack of data that typically confronts scholars who attempt to measure monitoring makes our proxy variables appropriate.

Second, although the bank is very representative of the domestic bank system in terms of strategy, credit/financial products and geographical coverage, because this study is based on one bank, our results cannot be generalized to all domestic banks.

Third, while we use a large sample of bank-firm relationships, our micro-data are organized as cross sectional data. Thus, because single cross-sectional data collection does not allow the analysis of change over time, the results should be interpreted with caution.

5. Conclusions

The level of the underground economy can influence how banks grant credit. In particular, the lack of formality may impede access to the credit market and lead to the credit rationing of informal firms due to their informational opaqueness. This friction represents one of the possible interactions between the credit market and the shadow economy.

According to our model, in the presence of a high level of informality, banks might find it optimal to choose a lending technology that involves the more intense monitoring of borrowers even if it is more costly. The logic is that if a large number of firms operate informally, it will be more difficult for banks to issue credit; this could reduce the volume of bank credit to the extent that it becomes more convenient to apply more in-depth monitoring. Given monitoring costs, the optimal lending technology is therefore influenced by the level of the underground economy as well as by other institutional factors. The primary direct implication is that policy interventions directed to reduce the informal economy should also reflect the structure of the credit market and the nature of the prevailing lending technology. A reduction of the underground economy would reduce lending costs, which in turn would favor the emergence of underground firms.

References

Agarwal, S., and Hauswald, R. (2010). Distance and Private Information in Lending. *Review of Financial Studies*, *23*(7), 2757–2788.

Ahn, S., and Choi, W. (2009). The role of bank monitoring in corporate governance: Evidence from borrowers earnings management behavior. *Journal of Banking and Finance*, *33*(2), 425–434.

Antunes, A. R., and Cavalcanti, T. V. de V. (2007). Start Up Costs, Limited Enforcement, and the Hidden Economy. *European Economic Review*, *51*(1), 203–224.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., and Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, *76*(2), 237–269.

Berger, A. N., and Udell, G. F. (1995). Relationship Lending and Lines of Credit in Small Firm Finance. *Journal of Business*, *68*(3), 351–381.

Berger, A. N., and Udell, G. F. (2006). A more complete conceptual framework for SME finance. *Journal of Banking & Finance*, *30*(11), 2945–2966. doi:10.1016/j.jbankfin.2006.05.008

Berkowitz, J., and White, M. J. (2004). Transactions Accounts and Loan Monitoring. *RAND Journal of Economics*, *35*(1), 69–84.

Besanko, D., and Thakor, A. V. (1987). Collateral and Rationing Sorting Equilibria in Monopolistic and Competitive Credit Markets. *International Economic Review*, *28*(3), 671.

Bester, H. (1987). The role of collateral in credit markets with imperfect information. *European Economic Review*.

Blackburn, K., Bose, N., and Capasso, S. (2012). Tax evasion, the underground economy and financial development. *Journal of Economic Behavior & Organization*, *83*(2), 243–253.

Blackwell, D. W., and Winters, D. B. (1997). Banking Relationships and the Effect of Monitoring on Loan Pricing. *Journal of Financial Research*, *20*(2), 275–289.

Boot, A. W. A. (2000). Relationship Banking: What Do We Know? *Journal of Financial Intermediation*, *9*(1), 7–25.

Boot, A. W. A., Milbourn, T. T., and Schmeits, A. (2006). Credit Ratings as Coordination Mechanisms. *Review of Financial Studies*, *19*(1), 81–118.

Boot, A. W. A., and Thakor, A. V. (1994). Moral Hazard and Secured Lending in an Infinitely Repeated Credit Market Game. *International Economic Review*, *35*(4), 899–920.

Boot, A. W. A., Thakor, A. V, and Udell, G. F. (1991). Secured Lending and Default Risk: Equilibrium Analysis, Policy Implications and Empirical Results. *Economic Journal*, *101*(406), 458.

Bose, N., Capasso, S., and Wurm, M. (2012). The Impact of Banking Development on the Size of the Shadow Economy. *Journal of Economic Studies*, *39*(6), 620–628.

Cai, J., Cheung, Y.-L., and Goyal, V. K. (1999). Bank monitoring and the maturity structure of Japanese corporate debt issues. *Pacific-Basin Finance Journal*, *7*(3), 229–250.

Capasso, S., and Jappelli, T. (2013). Financial development and the underground economy. *Journal of Development Economics*, *101*, 167–178.

Chan, Y.-S., and Kanatas, G. (1985). Asymmetric Valuations and the Role of Collateral in Loan Agreements. *Journal of Money, Credit and Banking*, *17*(1), 84–95.

Chen, Y. (2006). Collateral, loan guarantees, and the lenders' incentives to resolve financial distress. *Quarterly Review of Economics and Finance*, *46*(1), 1–15.

Cole, R. A. (1998). The importance of relationships to the availability of credit. *Journal of Banking & Finance*, *22*(6), 959–977.

Dabla-Norris, E., and Feltenstein, A. (2005). The Underground Economy and Its Macroeconomic Consequences. *Journal of Policy Reform*, *8*(2), 153–174.

Degryse, H., and Ongena, S. (2005). Distance, Lending Relationships, and Competition. *The Journal of Finance*, *LX*(1), 231–266.

Degryse, H., and Van Cayseele, P. (2000). Relationship Lending within a Bank-Based System: Evidence from European Small Business Data. *Journal of Financial Intermediation*, *9*(1), 90–109.

DeYoung, R., Glennon, D., and Nigro, P. (2008). Borrower--lender distance, credit scoring, and loan performance: Evidence from informational-opaque small business borrowers. *Journal of Financial Intermediation*, *17*(1), 113–143.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, *51*(3), 393–414.

Diamond, D. W. (1989). Reputation Acquisition in Debt Markets. *The Journal of Political Economy*, *97*(4), 828–862.

Diamond, D. W. (1991). Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt. *Journal of Political Economy*, *99*(4), 689–721.

Djankov, S., La Porta, R., Lopez-De-Silanes, F., and Shleifer, A. (2002). The regulation of entry. *Quarterly Journal Of Economics*, *117*(1), 1–37.

Elgin C., and Urasb B.R., (2013). Public debt, sovereign default risk and shadow economy, *Journal of Financial Stability*, 9 (4), 628-640.

Elsas, R., and Krahnen, J. P. (1998). Is relationship lending special? Evidence from credit-file data in Germany. *Journal of Banking & Finance*, *22*(10), 1283–1316.

Friedman, E., Johnson, S., Kaufmann, D., and Zoido-Lobaton, P. (2000). Dodging the Grabbing Hand: The Determinants of Unofficial Activity in 69 Countries. *Journal of Public Economics*, *76*(3), 459–493.

Gobbi, G. and R. Zizza (2007). Does the underground economy hold back financial deepening? evidence from the italian credit market. CEP Discussion Papers dp0789, Centre for Economic Performance, LSE.

Gorton, G., and Winton, A. (2003). Financial intermediation. In H. G. C. Milt & R. Stulz (Eds.), Handbook of the Economics of Finance (Volume 1A:, Vol. 1, pp. 431–552). Elsevier.

Hasan, I., Hoi, C.K., Wu, Q. and Zhang H. (2014). Beauty is in the eye of the beholder: the effect of corporate tax avoidance on the cost of bank loans, *Journal of Financial Economics*, 113 (1), 109–130.

Haubrich, J. G. (1989). Financial intermediation: Delegated monitoring and long-term relationships. *Journal of Banking & Finance*, *13*(1), 9–20.

Holmstrom, B., and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics*, *112*(3), 663–691.

Johnson, S., Kaufmann, D., & Shleifer, A. (1997). The Unofficial Economy in Transition. *Brookings papers on economic activity*, (2), 159–239.

Johnson, S., Kaufmann, D., Zoido-lobat, P., & Bank, T. W. (1998). Corruption , Public Finances and the Unofficial Economy.

Koenker, R., & Bassett Jr., G. (1978). Regression Quantiles. *Econometrica*, *46*(1), 33–50. Retrieved from http://www.jstor.org/stable/1913643

Koenker, R., & Hallock, K. F. (2001). Quantile Regression. *Journal of Economic Perspectives*, *15*(4), 143–156.

La Porta, R., & Shleifer, A. (2008). The unofficial economy and economic development. In *Brookings Papers on Economic Activity (2008)* (pp. 275–352). Brookings Institution Press.

Loayza, N. V, & Ranciere, R. (2006). Financial development, financial fragility, and growth. *Journal of Money Credit and Banking*, *38*(4), 1051–1076. doi:10.1353/mcb.2006.0060

Mester, L. J., Nakamura, L. I., and Renault, M. (2007). Transactions Accounts and Loan Monitoring. *Review of Financial Studies, 20*(3), 529–556.

Petersen, M. A., and Rajan, R. G. (1994). The Benefits of Lending Relationships: Evidence from Small Business Data. *The Journal of Finance*, *49*(1), 3–37.

Rajan, R. G. (1992). Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt. *The Journal of Finance*, *47*(4), 1367–1400.

Ramakrishnan, R. T. S., and Thakor, A. V. (1984). Information Reliability and a Theory of Financial Intermediation. *The Review of Economic Studies*, *51*(3), 415–432.

Sharpe, S. A. (1990). Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships. *The Journal of Finance, 45*(4), 1069–1087.

Stein, J. C. (2002). Information Production and Capital Allocation: Decentralized versus Hierarchical Firms. *The Journal of Finance, 57*(5), 1891–1921.

Straub, S. (2005). Informal sector: the credit market channel. *Journal of Development Economics*, *78*(2), 299–321.

Von Thadden, E.-L. (1995). Long-Term Contracts, Short-Term Investment and Monitoring. *The Review of Economic Studies*, *62*(4), 557–575.

Table 1
Summary Variables

	Description	Mean	Percentiles 5th	50th	95th	Observations
$DEBT\_TO\_SALES_{IJ}$	The ratio between the bank debt and the sales of firm *i* (*i*=1…29,568) for bank j (j=1, …8) at 31 Dec. 2008	0.37	0.02	0.15	1.38	30,505
IRR_JOB	The share of irregular workers. The ratio between irregular and regular labor force units in 2008.	11.67	8.5	8.5	18.6	
$DURATION_{ij}$	The natural log of the length (in years) of the credit relationship between bank *j* (*j=1…*8) and firm *i* (*i*=1…29,568) at the end of 2008.	1.94	0.69	1.94	3.09	30,505
$BANKS_i$	The natural log of lending banks for firm *i* (*i*=1…29,568).	1.40	0.69	1.38	2.56	30,505
$RISK_{ij}$	The natural log of the banks' internal borrower rating system is composed of 10 risk classes for solvent borrowers (i.e., 1 = the least risky class; 10 = the most risky).	1.49	0	1.34	2.22	30,505
$COLLAT_{ij}$	A dummy that has the value 1 if firm *i* has collateral with bank *j*.	0.034	0	0	0	30,505
$DISTANCE_{ij}$	The natural log of (1+km), where km indicates the kilometers between the province of the local branch with which firm *i* has a relationship and the city of bank *j*'s headquarters.	3.35	0	3.89	6.02	30,505
$DENSITY_j$	The natural log of the number of branches for bank j per 1000 firms at the province level.	0.78	0.05	0.68	1.47	29,568
LARGE	Dummy that has the value 1 if the firm's size is classified as "Large" by internal bank criteria.	0.01	0	0	0	30,505
MEDIUM	Dummy that has the value 1 if the firm's size is classified as "Medium" by internal bank criteria.	0.25	0	0	1	30,505
SMALL	Dummy that has the value 1 if the firm's size is classified as "Small" by internal bank criteria.	0.39	0	0	1	30,505
VERY SMALL	Dummy that has the value 1 if the firm's size is classified as "Very Small" by internal bank criteria.	0.32	0	0	1	30,505

Table 2
Quantile regression estimates of factors affecting *Debt_to_Sales* values.

	Selected Quantiles				
	10	25	50	75	90
Shadow economy					
IRR_JOB	0.0006 (0.1192)	0.0005 (0.2467)	0.0004 (0.5515)	0.0040*** (0.0075)	0.0115*** (0.0006)
Monitoring					
DURATION	0.0422*** (0.0000)	0.0480*** (0.0000)	0.0573*** (0.0000)	0.0909*** (0.0000)	0.1214*** (0.0007)
DURATION^2	-0.0089*** (0.0000)	-0.0099*** (0.0000)	-0.0113*** (0.0000)	-0.0194*** (0.0000)	-0.0272*** (0.0017)
BANKS	-0.0085*** (0.0000)	-0.0324*** (0.0000)	-0.0796*** (0.0000)	-0.1737*** (0.0000)	-0.3672*** (0.0000)
RISK	0.0063*** (0.0000)	0.0131*** (0.0000)	0.0277*** (0.0000)	0.0627*** (0.0000)	0.1361*** (0.0000)
Bank and loan-specific variables					
COLLAT	-0.0013 (0.6221)	0.0127*** (0.0001)	0.0528*** (0.0000)	0.1709*** (0.0000)	0.5340*** (0.0000)
DISTANCE	-0.0017*** (0.0000)	-0.0021*** (0.0000)	-0.0039*** (0.0000)	-0.0053*** (0.0000)	-0.0091*** (0.0004)
DENSITY	0.0052*** (0.0000)	0.0090*** (0.0000)	0.0117*** (0.0000)	0.0168*** (0.0002)	0.0049 (0.6068)
Constant	-0.0279* (0.0942)	0.0145 (0.4817)	0.0973*** (0.0006)	0.2375*** (0.0008)	0.9610*** (0.0000)
n-1 Banks Dummies (7)	Yes	Yes	Yes	Yes	Yes
n-1 Firm's size Dummies (3)	Yes	Yes	Yes	Yes	Yes
n-1 Industry Dummies (13)	Yes	Yes	Yes	Yes	Yes
Observations	29,568	29,568	29,568	29,568	29,568

This table reports the estimation results of a quantile regression. The dependent variable (*Debt_to_Sales*) and the other variables are described in Table 1. Data are extracted from the client folders of a banking group (composed of 8 banks) and contain information about the bank-firm relationships of 29,568 firms belonging to 14 different macro-industries. The P-values are reported in parentheses. ***Denotes statistical significance at the 0.01 level of confidence, ** at the 0.05 level of confidence and * at the 0.10 level of confidence.

Table 3
Quantile regression with interaction terms among monitoring variables and shadow economy.

	Selected Quantiles					
	Model (1)		Model (2)		Model (3)	
quantile	Q75	Q90	Q75	Q90	Q75	Q90
Shadow economy						
IRR_JOB	0.0063***	0.0300***	-0.002	-0.000	0.0022	-3.5E-05
	(0.0004)	(0.000)	(0.1947)	(0.8106)	(0.2414)	(0.9936)
Monitoring						
DURATION	0.0878***	0.0874**	0.0369*	0.0195	0.0913***	0.1132***
	(0.000)	(0.0186)	(0.0504)	(0.6207)	(0.000)	(0.0017)
$DURATION^2$	-0.0188***	-0.0195**	-0.0174***	-0.0225	-0.0196***	-0.0252***
	(0.000)	(0.0294)	(0.000)	(0.0097)	(0.000)	(0.0038)
BANKS	-0.1575***	-0.2338***	-0.1723***	-0.3669	-0.1738***	-0.3648***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RISK	0.0622***	0.1318***	0.0617***	0.1353	0.0513***	0.0621***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
IRR_JOB x BANKS	-0.0016*	-0.0124***				
	(0.0644	(0.000)				
IRR_JOB x DURATION			0.0044***	0.0085***		
			(0.000)	(0.000)		
IRR_JOB x RISK					0.0011	0.0075***
					(0.1285)	(0.000)
Bank and loan-specific variables						
COLLAT	0.1683***	0.5517***	0.1702***	0.5240	0.1700***	0.5403***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DISTANCE	-0.0055***	-0.0093***	-0.0049***	-0.0082	-0.0056***	-0.0081***
	(0.000)	(0.0004)	(0.0001)	(0.0015)	(0.000)	(0.0015)
DENSITY	0.0162***	0.0110	0.0227***	0.0135	0.0154***	0.0076
	(0.0002)	(0.2597)	(0.000)	(0.1614)	(0.0003)	(0.426)
Constant	0.2409***	0.7192***	0.2991***	1.0802***	0.6111***	1.5818***
	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
n-1 Banks Dummies (7)	Yes	Yes	Yes	Yes	Yes	Yes
n-1 Firm's size Dummies (3)	Yes	Yes	Yes	Yes	Yes	Yes
n-1 Industry Dummies (13)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,568	29,568	29,568	29,568	29,568	29,568

This table reports the estimation results of a quantile regression including interaction between the shadow economy and the monitoring variables. The results are presented for the 75th and 90th quantiles (Q75 and Q90), while results for the lower quantiles are omitted for brevity (and available upon request). The P-values are reported in parentheses. ***Denotes statistical significance at the 0.01 level of confidence, ** at the 0.05 level of confidence and * at the 0.10 level of confidence.

Table 4
Robustness check.
Baseline regression with a different variable of shadow economy (CASH).

	Selected Quantiles				
	10	25	50	75	90
Shadow economy					
CASH	-0.0018	-0.0119	-0.0267	0.0760	0.2573**
	0.8917)	(0.4426)	(0.2068)	(0.1331)	(0.0193)
Monitoring					
DURATION	0.0413***	0.0486***	0.0583***	0.0933***	0.1382***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
DURATION^2	-0.0087***	-0.0101***	-0.0116***	-0.0202***	-0.0307***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
BANKS	-0.0086***	-0.0330***	-0.0800***	-0.1741***	-0.3717***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RISK	0.0063***	0.0133***	0.0278***	0.0625***	0.1368***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Bank and loan-specific variables					
COLLAT	-0.0015	0.0131***	0.0527***	0.1709***	0.5497***
	(0.5667)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
DISTANCE	-0.0016***	-0.0021***	-0.0039***	-0.0053***	-0.0093***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
DENSITY	0.0061***	0.0098***	0.0122***	0.0172***	0.0054
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.5561)
Constant	-0.0160	0.0297	0.1164***	0.2754***	1.0427***
	(0.3264)	(0.1431)	(0.0000)	(0.0001)	(0.0000)
n-1 Banks Dummies (7)	Yes	Yes	Yes	Yes	Yes
n-1 Firm's size Dummies (3)	Yes	Yes	Yes	Yes	Yes
n-1 Industry Dummies (13)	Yes	Yes	Yes	Yes	Yes
Observations	29,568	29,568	29,568	29,568	29,568

This table reports the estimation results of the baseline quantile regression after the inclusion of a different variable for the shadow economy. The new variable is CASH, which is the ratio for the income received in cash to the total income. The P-values are reported in parentheses. ***Denotes statistical significance at the 0.01 level of confidence, ** at the 0.05 level of confidence and * at the 0.10 level of confidence.

Table 5
Quantile regression with interaction terms among monitoring variables and CASH

	Selected Quantiles					
	Model (1)		Model (2)		Model (3)	
quantile	Q75	Q90	Q75	Q90	Q75	Q90
Shadow economy						
CASH	0.1145	0.6871***	-0.0583	0.0147	0.0599	0.0054
	(0.0672)	(0.0000)	(0.3513)	(0.9151)	(0.3781)	(0.9702)
Monitoring						
DURATION	0.0916***	0.0950***	0.0728***	0.0887**	0.0934***	0.1315***
	(0.0000)	(0.0074)	(0.0000)	(0.0223)	(0.0000)	(0.0002)
$DURATION^2$	-0.0198***	-0.0206**	-0.0192***	-0.0258***	-0.0202***	-0.0291***
	(0.0000)	(0.0164)	(0.0000)	(0.0040)	(0.0000)	(0.0005)
BANKS	-0.1697***	-0.3147***	-0.1734***	-0.3741***	-0.1742***	-0.3707***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RISK	0.0626***	0.1382***	0.0619***	0.1366***	0.0606***	0.1103***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CASH x BANKS	-0.0213	-0.2617***				
	(0.4319)	(0.0001)				
CASH x DURATION			0.0812***	0.1502***		
			(0.0005)	(0.0035)		
CASH x RISK					0.0097	0.1471***
					(0.6962)	(0.0042)
Bank and loan-specific variables						
COLLAT	0.1693***	0.5515***	0.1700***	0.5515***	0.1694***	0.5387***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
DISTANCE	-0.0052***	-0.0079***	-0.0046***	-0.0085***	-0.0055***	-0.0085***
	(0.0000)	(0.0017)	(0.0002)	(0.0013)	(0.0000)	(0.0005)
DENSITY	0.0179***	0.0145	0.0238***	0.0082	0.0171***	0.0075
	(0.0001)	(0.1212)	(0.0000)	(0.4060)	(0.0002)	(0.4152)
Constant	0.2721***	0.9256***	0.3041***	1.0908***	0.2773***	1.0815***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
n-1 Banks Dummies (7)	Yes	Yes	Yes	Yes	Yes	Yes
n-1 Firm's size Dummies (3)	Yes	Yes	Yes	Yes	Yes	Yes
n-1 Industry Dummies (13)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,568	29,568	29,568	29,568	29,568	29,568

This table reports estimation results of a quantile regression including interaction among monitoring variables and shadow economy (using CASH). The results are presented for the 75th and 90th quantiles (Q75 and Q90), while results for the lower quantiles are omitted for brevity (and available upon request). The P-values are reported in parentheses. ***Denotes statistical significance at the 0.01 level of confidence, ** at the 0.05 level of confidence and * at the 0.10 level of confidence.

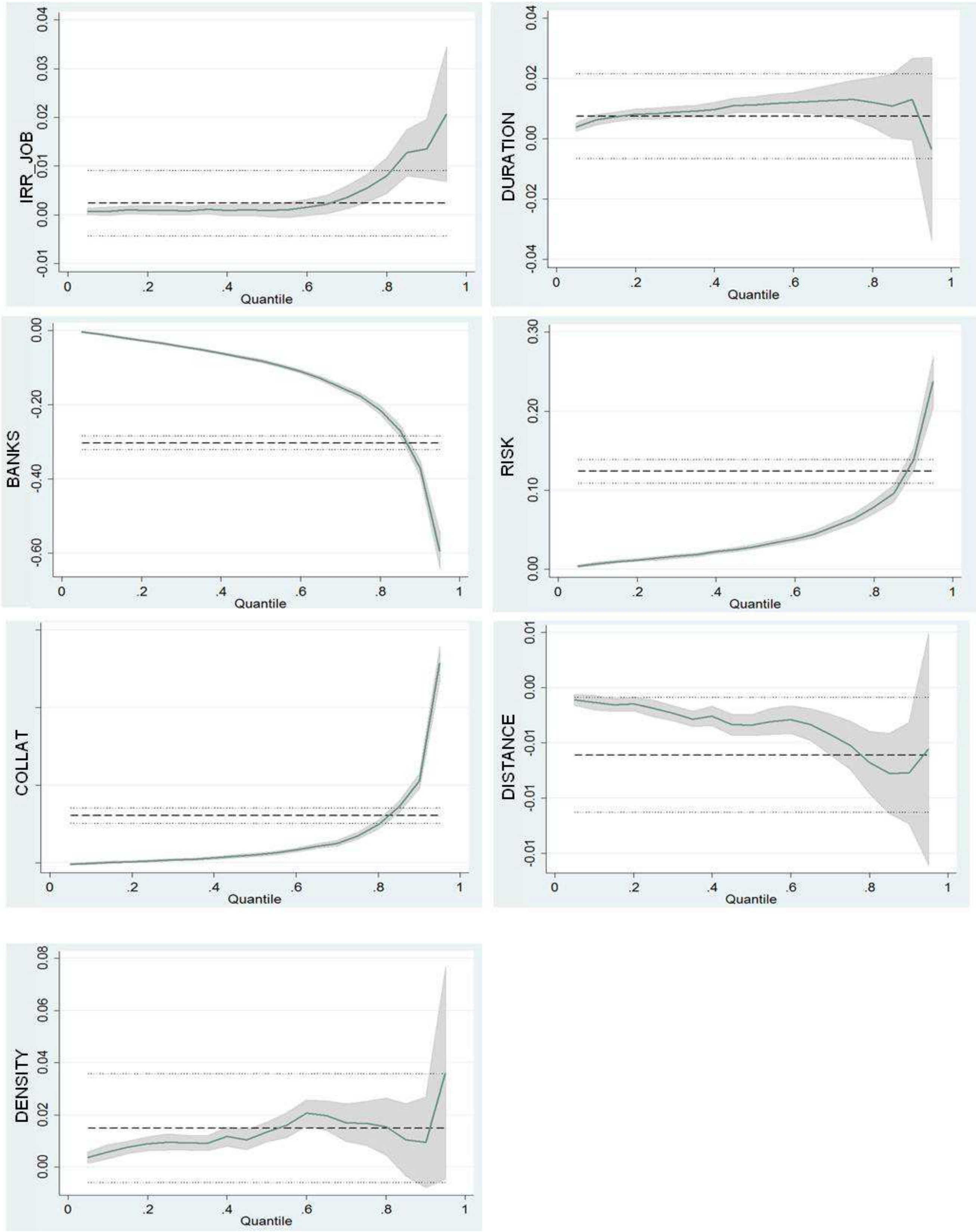


Fig. 1 Coefficients and their confidence band estimated by different quantiles