**Does IRS monitoring matter for the cost of bank loans?**

**by**

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**Abstract** We show that IRS monitoring exerts a significantly negative effect on the cost of syndicated loans. A one standard deviation increase in the probability of an IRS audit decreases loan spreads by around nine basis points. We also find that this effect is stronger for borrowers with better lending relationships and credible access to public markets. These results indicate that IRS monitoring could increase the bargaining power of borrowers and restrain banks from extracting informational rents from their lending relationships. Thus, they provide a novel insight into how IRS monitoring could lower the cost of financing from the banking system.

**Keywords** Syndicated loans ● IRS monitoring ● Information asymmetry ● Lending relationships

**JEL Classification** G21 ● H25 ● H26

**1 Introduction**

Does monitoring from the US Internal Revenue Service (IRS) reduce the cost of bank loans? The IRS and its tax enforcement provide external monitoring to US corporations. External monitors help reduce information asymmetries in the financial and credit markets. For example, Dyck et al. (2010) show that external monitoring mechanisms such as credit rating agencies, the SEC, institutional ownership, and others collectively identify around 40% of corporate fraud cases in the US. Several studies also find that external monitors improve the corporate information environment and exert a chilling effect on the opportunistic behavior of managers to misuse (divert) corporate income for personal benefit (Bannier and Hirsch 2010; Boone and White 2015; Chen et al. 2015). The vital role of external monitoring in alleviating information asymmetries induces banks to charge borrowers a lower cost for loans (Booth 1992; Sufi 2007; Cen et al. 2016; Ni and Yin 2018). However, to the best of our knowledge, no study has investigated the effects of IRS monitoring on the cost of bank loans.

An examination of these effects is important for two reasons. The first is that debt is the most important source of new financing for corporations in the US. Around 75% of new corporate financing comes in the form of debt (Contessi et al. 2013). Moreover, most of this financing comes from bank loans, even for large public corporations (Bharath et al. 2008; Hasan et al. 2014). This fact highlights the significant role that bank financing plays in US corporations and justifies the growing research interest in its determinants. Therefore, from the perspectives of managers and public policy, exploring the relationship between IRS monitoring and the cost of bank loans for US corporations is useful.

The second is an ongoing policy debate in the US about the future of the IRS. The US Senate passed the *Inflation Reduction Act* in August 2022, which contains provisions for a significant increase in IRS funding ($80bn in total, $45.6bn for enforcement). In previous years, the overall IRS budget declined from around $14 billion in 2010 to $12 billion in 2018 (ProPublica 2019). In addition, its tax enforcement budget also experienced a 23% decline over the same period. Funding has an impact on the ability of the agency to enforce taxes. Nessa et al. (2020) show that fewer IRS resources weaken tax enforcement by decreasing the audit rate of tax returns. Indeed, the Transactional Records Access Clearing House (2019) reports that corporations' IRS audit rates dropped significantly from 2010 to 2018. This situation has raised the interest of researchers to examine the efficacy of the IRS and the potential effects that its funding and monitoring capacity could have on the economy. We aim to add to this debate by exploring the effects of IRS monitoring on the cost of bank loans. We pose the question-should firms welcome or fear the possibility of increased IRS monitoring? Providing evidence that IRS monitoring decreases the cost of bank financing for US corporations could form an additional argument in favor of the agency’s activities.

The literature has shown that monitoring by a tax enforcement agency can reduce information asymmetry. The main concern of the tax authorities is the compliance of firms with the tax code. However, managers that engage in aggressive tax practices try to distort firms' information environment to conceal such activities (Leuz et al. 2003; Desai and Dharmapala 2006). Furthermore, this obfuscation of firms' information environment facilitates insiders' misuse of the firm's income. Hence, a by-product of monitoring by the tax agency is the improvement in firms' information environment (Desai et al. 2007; Hanlon et al. 2014; Bauer et al. 2020) and a decrease in the potential for managerial diversion (Desai and Dharmapala 2009; Mironov 2013). Therefore, our first hypothesis (***H.1***) is that IRS monitoring negatively affects the cost of bank loans by reducing information asymmetry.

We also investigate two potential mechanisms through which this reduction could prompt banks to decrease loan prices. The first is that IRS monitoring could enable banks to incur savings in screening and monitoring costs. Banks could consequently pass these savings on to borrowers through lower loan prices. The second is that IRS monitoring could enhance the bargaining power of borrowers *vis-à-vis* banks. Factors that decrease information asymmetries induce the markets for external financing to be more contestable (Mazumdar and Sengupta 2005; Schenone 2010; Kim et al. 2011; Florou and Kosi 2015; Cahn et al. 2021; Saidi and Zaldokas 2021). Therefore, IRS monitoring could ease borrowers' access to alternative sources of external financing (e.g., other banks and the public markets). Some studies have shown that IRS monitoring decreases the costs of bonds (Guedhami and Pittman 2008) and equity (El Ghoul et al. 2011) but increases bank lending (Gallemore and Jacob 2020). Consequently, borrowers' bargaining power could increase because banks, when negotiating loan prices, may consider the alternative options for external financing that borrowers have (Sharpe 1990; Rajan 1992).

To identify which of these two mechanisms is the dominant driver of the potentially negative association between IRS monitoring and the cost of bank loans, we rely on theories about lending relationships. When banks have repeated interactions with the same borrower, they accumulate valuable private information on the former (Diamond 1984; Rajan 1992). Therefore, strong lending relationships could reduce banks' screening and monitoring costs which induce them to decrease loan prices (Boot and Thakor 1994; Petersen and Rajan 1994; Boot 2000; Bharath et al. 2011). Hence, if the dominant channel is the decrease in screening and monitoring costs, we predict this association will be less evident for borrowers with strong lending relationships with banks (hypothesis ***H.2A***).

On the other hand, the private information on borrowers that banks collect through strong lending relationships enables the latter to have an informational advantage compared to other providers of external financing. Banks could exploit this informational advantage when pricing the loans that they are making to relationship borrowers (Sharpe 1990; Rajan 1992; Degryse and Ongena 2005; Ioannidou and Ongena 2010; Schenone 2010; Mattes et al. 2013; Hasan et al. 2019). By decreasing information asymmetries, IRS monitoring could erode relationship banks' informational advantage over other providers of external financing, such as private lenders and the public markets. Hence, the borrowers' bargaining power *vis-à-vis* banks with which they have strong lending relationships could increase and facilitate a decrease in loan prices. Thus, if the dominant mechanism is the increase in the borrowers' bargaining power, we predict this association will be more evident for borrowers that have strong lending relationships with banks (hypothesis ***H.2B***).

For our examination, we source data from Thomson One Banker and construct a sample of 7,054 syndicated loan facilities to 1,335 US firms from 1993 to 2017.[[1]](#footnote-1) Using the syndicated loan market provides some advantages in investigating the determinants of bank loans. We have detailed data on bank loans, such as their price, size, maturity, and information on borrowers and lenders. Furthermore, according to Sufi (2007), the syndicated loan market provides a promising ground for investigating information asymmetry because firms from the whole credit spectrum (e.g., private, public, rated, and unrated) use this method of external financing.

We measure the cost of bank loans as the *all-in-spread* that is the interest payment in basis points above LIBOR plus the annual fee (in basis points) for a loan facility of a firm (Hasan et al. 2014). We use the yearly rate of face-to-face corporate audits by the IRS to capture its monitoring. These audit rates use IRS records about the corporate tax returns received and audits completed by size class (eight classes based on total assets) each year. Thus, the *all-in-spread* varies with the size class and the calendar year. We source the data on IRS audit rates from the Transactional Records Access Clearing House (TRAC) of Syracuse University. This measure is widely used in the literature (Guedhami and Pittman 2008; El Ghoul et al. 2011; Hoopes et al. 2012; Hanlon et al. 2014; Bauer et al. 2020) to gauge the level of monitoring of US firms by the IRS.

After controlling for several characteristics of both borrowing firms and loans, the main finding is that IRS monitoring exerts a negative and significant effect on the cost of syndicated loans. The baseline estimates show that a one standard deviation increase in the IRS audit rate results in an 8.84 basis points reduction in the loan spreads. Considering the average size ($522 million) and the average maturity (3.4 years) of loans in our sample, this reduction in loan spreads translates into $1.49 million in interest savings on average. This finding supports ***H.1*** that more stringent IRS monitoring reduces loan spreads for US firms.

We use three lending relationship variables to test ***H.2A*** and ***H2.B***. Using models with interaction terms, we show that the negative effect of the IRS audit rate on the cost of bank loans is more pronounced for firms with a stronger lending relationship with the lead bank that provides the loan. This finding is consistent with ***H2.B*** and provides empirical support to the argument that the dominant mechanism driving the negative association between IRS monitoring and the cost of bank loans is the increase in borrowers' bargaining power *vis-à-vis* banks. Thus, IRS monitoring restricts banks' ability to extract informational rents from their relationship borrowers.

In further tests, we show that the negative interaction between IRS monitoring and the lending relationship measures is more evident for firms with credible access to the public markets for external financing (i.e., for listed firms, firms that have an investment-grade S&P credit rating, and firms belonging to the S&P 500 index). This finding is consistent with the idea that external monitoring is more useful for the public markets than for private lenders because of the former’s weak monitoring incentives and the substantial need for high-quality publicly available hard information (Diamond 1984; Boot and Thakor 2009; Bharath and Hertzel 2019; Liberti and Petersen 2019). This result is also consistent with the studies that show that IRS monitoring facilitates less costly access to the equity and public debt markets (Guedhami and Pittman 2008; El Ghoul et al. 2011), which enhances the bargaining power argument.

We run numerous additional tests and robustness exercises to support the baseline results. One challenge is that the primary IRS monitoring variable of size class relates by construction to the size of the borrowing firms. For this reason, in the baseline models, we control for size by using the natural log of the total assets of the borrowing firms. Furthermore, we add size class fixed effects to the baseline specifications to capture any systematic relationship between the costs of bank loans and borrowing firms in each IRS-defined size class. In further robustness checks, we also perform estimations where we add the squared and cubed values of the size to account for potential non-linearities. Also, we control for alternative measures of the size of the borrowing firms, such as the natural logs of sales and equity, and run models with time trends for each IRS-defined size class.

The results are robust when we use alternative IRS monitoring proxies, as in Guedhami and Pittman (2008), that do not hinge on the IRS-defined size class of the borrowing firm. For example, we use IRS staffing levels, penalties, and prosecutions as monitoring proxies. In another test, we introduce a geographic source of variation in IRS monitoring to our models. We find that the negative association between IRS monitoring and the cost of bank loans becomes more pronounced for firms located in states with a larger number of IRS offices.

Another challenge is potential endogeneity through a feedback effect between the cost of bank loans and IRS monitoring. For example, the cost of bank financing could affect the availability of funds firms can use to engage in tax-related lobbying (see, e.g., Hill et al. 2013; Kim and Zhang 2016). For this reason, we also perform two-stage least squares instrumental (2SLS-IV) variable estimations. To this end, we use two instruments. For the first instrument, we follow the study of Hoopes et al. (2012) and use the lagged number of corporate tax returns filed in each IRS-defined size class. Further, we construct a second instrument by assigning to each firm the average lagged audit rate of all the size classes, excluding the audit rate of the specific size class to which a firm belongs.[[2]](#footnote-2) The results from the 2SLS-IV estimations provide further evidence in support of the baseline findings.

Further, the negative relationship between IRS monitoring and the cost of bank loans remains robust to additional tests. These are the alternative ways of clustering of the standard errors (at the size class and year levels and the borrowing firm and bank levels), such as dropping from the sample observations the largest size class that the IRS audits (i.e., firms with a size larger than $250 million that are the majority of the sample) while controlling for syndicate size and the index of the state-level tax climate for businesses.

We also test ***H.1***, ***H.2A***, and ***H.2.B*** for the non-price terms of the loan contracts. We find that more stringent IRS monitoring decreases the probability that a loan will contain covenants (***H.1***). Furthermore, we show that the negative association of IRS monitoring with the probability that loans will contain covenants becomes more prominent for firms with stronger lending relationships (***H2.B***).

This study contributes to the literature in several ways. It belongs to the literature that examines the role of external monitors on the cost of bank financing. Several studies explore the effect of external monitoring mechanisms such as credit rating agencies, the SEC, shareholder litigation rights, financial analyst coverage, the media, and principal customers on the cost of bank loans (e.g., Booth 1992; Sufi 2007; Cen et al. 2016; Bushman et al. 2017; Coyne and Stice 2018; Ni and Yin 2018). We add to this literature by finding that the IRS provides valuable external monitoring that reduces bank financing costs for US firms in the syndicated loan market.

This study also complements those of Guedhami and Pittman (2008) and El Ghoul et al. (2011), who examine the effect of IRS monitoring on the cost of bonds and equity, respectively. We do so in the challenging setting of syndicated lending and provide a novel insight into how IRS monitoring reduces the cost of corporate financing through the banking system. We show that this negative association becomes more pronounced for firms with stronger bank lending relationships. This finding is also more evident for firms with credible access to the equity and public debt markets. Our results show that banks acknowledge the increased bargaining power of borrowers that IRS monitoring facilitates, especially for borrowers with access to the public markets. This increased bargaining power renders banks less able to extract informational rents from their lending relationships.

Thus, we also contribute to the studies that use the setting of lending relationships to examine the borrowers' bargaining power as a mechanism that affects the cost of bank loans (e.g., Schenone 2010; Saidi and Zaldokas 2021; Cahn et al. 2021). These studies show that factors that reduce information asymmetries, such as increased corporate disclosure after an IPO (Schenone 2010), increased innovation disclosure (Saidi and Zaldokas 2021), and improvement in rating information (Cahn et al. 2021), erode the informational advantage of relationship banks' *vis-à-vis* other providers of external financing. Hence, borrowers face decreased loan prices from their relationship banks. Our findings are consistent with the results of these studies from the standpoint of IRS monitoring.

We also add to the literature that examines the effect of tax-related issues on the cost of bank loans (e.g., Lim 2011; Hasan et al. 2014; Isin 2018). For example, Hasan et al. (2014) and Isin (2018) find a positive relationship between tax avoidance and bank loan spreads. We add to this literature by finding that IRS monitoring decreases the cost of bank loans. By controlling for several tax avoidance measures, we also show that the negative effect of IRS monitoring is incremental to the effect of tax avoidance. Hence, our findings indicate that IRS monitoring plays a broader monitoring and informational role in the loan market, consistent with the studies showing that tax enforcement benefits the corporate information environment and disciplines managers (Desai et al. 2007; Hanlon et al. 2014).

One could view the findings of our study in conjunction with that of Gallemore and Jacob (2020). They find that IRS monitoring induces banks to increase the loan supply to small and midsized enterprises (SMEs). Together, these studies demonstrate that the IRS prompts positive spillovers to the US economy through the banking sector beyond the traditional role of a tax enforcement agency. Using confidential IRS data, Nessa et al. (2020) estimate a conservative 2:1 return on enforcement for the audits of large US corporations. The return on enforcement measure represents the ratio of the expected increase in tax revenue to the cost of IRS audits and other related expenses. Hence, enhancing the monitoring resources of the IRS through the *Inflation Reduction Act* of 2022 could potentially benefit both government finances and the development of US corporations from a bank credit standpoint. Thus, our findings could also contribute to the public policy debate about the future of the IRS.

The rest of the study is organized as follows: Section 2 presents some theoretical considerations and develops the hypotheses. Section 3 presents the data, research design, and descriptive statistics. Sections 4 and 5 present the main findings and a summary of robustness tests, respectively, while Section 6 concludes.

**2 Hypotheses development**

**2.1 The association of IRS monitoring with the cost of bank loans**

IRS monitoring could facilitate a decrease in information asymmetries. This decrease could stem from an improved corporate information environment under higher levels of tax enforcement. Desai and Dharmapala (2006) posit that aggressive tax practices induce a complex and opaque information environment that is aimed at reducing the possibility of detection from the tax agency. The tools to achieve such an obfuscation comprise earnings manipulations, related party transactions, and the hoarding of information (Wilson 2009; Chen et al. 2010; Kim et al. 2011). Monitoring from the tax agency could restrict these practices (Hoopes et al. 2012). Thus, a beneficial spillover effect of tax enforcement is that it improves the quality of the information available to outsiders (Desai et al. 2007; Hanlon et al. 2014). Also, tax enforcement could lessen information asymmetry by reducing managers' incentives to divert firm resources for their benefit. Desai and Dharmapala (2009) maintain that stricter tax enforcement prevents firms' insiders from misusing corporate income. Managers could exploit the obfuscation of the firms' information environment that stems from aggressive tax practices to conceal rent-seeking from outsiders (Leuz et al. 2003). Jia and Gao (2021) provide recent evidence that US firms favor this source of managerial diversion. Therefore, by improving firms' information environment, tax enforcement also reduces the potential for managerial diversion (El Ghoul et al. 2011; Mironov 2013). Overall, IRS monitoring could decrease information asymmetry by improving the quality of corporate information and restricting the potential for managerial diversion.

A decrease in information asymmetry could facilitate two potential channels through which IRS monitoring could decrease the cost of bank loans. The first is that the improved corporate information environment may enable banks to dedicate fewer resources to their screening and monitoring when evaluating borrowers. The second potential channel is an increase in borrowers' bargaining power *vis-à-vis* banks. When setting loan prices, banks consider the degree to which borrowers could access alternative sources of external financing (e.g., other banks or the public markets) at competitive prices (Sharpe 1990; Rajan 1992). An improvement in borrowers' information environment could ease such access and prompt these alternates to become more contestable (Mazumdar and Sengupta 2005; Schenone 2010; Kim et al. 2011; Florou and Kosi 2015; Cahn et al. 2021; Saidi and Zaldokas 2021).

Several studies have shown that the public and private markets for external financing value IRS monitoring. Regarding the public markets, Guedhami and Pittman (2008) show that IRS monitoring decreases the cost of bonds, while El Ghoul et al. (2011) find a negative association between IRS monitoring and the cost of equity. Bauer et al. (2020) show a negative relationship between IRS monitoring and the crash risk of stocks. Concerning the private debt market, Gallemore and Jacob (2020) find that banks increase their lending activity when IRS monitoring is more stringent.[[3]](#footnote-3) Together, these studies indicate that IRS monitoring could facilitate easier access to the public and private markets of external financing.[[4]](#footnote-4) Improved access to alternative sources could increase the bargaining power of borrowing firms that may push banks to reduce their costs to maintain their customer base.

Based on the above discussion, we conjecture that more stringent IRS monitoring could lead to lower bank loan spreads for firms. Our first and main hypothesis (***H.1***), therefore, is the following:

***H.1 IRS monitoring has a negative association with the cost of bank loans.***

**2.2 The conditioning effect of lending relationships on the association of IRS monitoring with the cost of bank loans**

To identify the dominant channel through which IRS monitoring could reduce the cost of bank loans, we examine if lending relationships could influence the association between IRS monitoring and loan spreads. Using lending relationships as a potential mediating factor to investigate which of the two potential channels prevails has a solid theoretical basis.

The literature has identified two distinct but coexisting features of lending relationships that relate information asymmetries with screening and monitoring costs and borrowers' bargaining power (Alexandre 2014). The first feature associates the decrease in information asymmetry that lending relationships prompt with a reduction in screening and monitoring costs. Repeated lending interactions with the same firms give banks access to valuable private information about borrowers that otherwise would be costly to obtain (Diamond 1984; Rajan 1992). As lending relationships become intense, banks incur savings in screening and monitoring borrowers. Several studies have shown that banks pass these savings on to borrowers through decreased loan prices (Boot and Thakor 1994; Petersen and Rajan 1994; Boot 2000; Bharath et al. 2011). The above arguments indicate that IRS monitoring may be less valuable as a mechanism that could assist banks' screening and monitoring when lending relationships are more potent. Hence, if this reduction is the dominant channel through which IRS monitoring decreases bank loans' cost, we predict that this effect will be less evident for borrowers with stronger lending relationships.

Hence, we formulate hypothesis ***H.2A*** as follows:

***H.2A The negative association of IRS monitoring with the cost of bank loans will be weaker for loans given to firms with stronger lending relationships.***

Another strand of the literature posits that strong lending relationships enable banks to extract rents from relationship borrowers (Sharpe 1990; Rajan 1992; Degryse and Ongena 2005; Ioannidou and Ongena 2010; Schenone 2010; Hasan et al. 2019). Through repeated lending transactions with borrowers, informed banks gain access to proprietary information that is unavailable to other uninformed providers of external financing. This access, in turn, increases the informational advantage of these banks *vis-à-vis* other providers (Schenone 2010; Dass and Massa 2011). As a result, lending relationships could enable the extraction of informational rents in the form of higher loan spreads. This is the so-called *lock-in* or *hold-up* effect that relationship borrowers could face due to the higher information asymmetry between them and outside providers of external financing in comparison with relationship banks (Sharpe 1990; Rajan 1992).

Based on this discussion, the informational advantage of relationship banks indicates decreased bargaining power for relationship borrowers. When negotiating loan prices, relationship banks account for the degree to which their informational advantage limits the ability of relationship borrowers to access alternative sources of external financing at competitive prices. Several studies have shown that the factors that improve borrowers' information environment have led to a decrease in the informational advantage of relationship banks *vis-à-vis* other providers of external financing (e.g., outside banks and the public markets), thus increasing borrowers' bargaining power. This increased power could translate into lower loan spreads for relationship borrowers.

Schenone (2010) shows that positive information shocks about corporations decrease relationship banks' informational advantage and restrict their ability to "hold-up" borrowers. In particular, Schenone (2010) finds that in the period after a relationship borrowers' IPO, increased corporate disclosure levelled the informational playing field between relationship banks and outside lenders. Consequently, relationship borrowers' bargaining power increases, and they enjoy lower loan spreads from their relationship banks. Saidi and Zaldokas (2021) show that after the passage of legislation that increases public disclosure about corporate innovation (the American Inventor's Protection Act of 1999 - AIPA), relationship banks were less able to "hold-up" their relationship borrowers. They find that relationship banks significantly decrease the loan spreads for their relationship borrowers in the period after AIPA. They also show that AIPA has facilitated easier access for relationship borrowers to outside banks and the public markets. Cahn et al. (2021) provide analogous evidence from the French market. They find that a refinement in the rating certifier's information reduces the ability of relationship banks to extract informational rents from affected relationship borrowers and improves access to alternative providers of external financing.[[5]](#footnote-5)

Similar to these studies, we posit that IRS monitoring could diminish relationship banks' informational advantage *vis-à-vis* alternative providers of external financing by decreasing information asymmetries. This decrease in relationship banks' informational advantage could make credit and public financing markets more contestable. This is plausible because research has shown that these providers appreciate the beneficial effects of IRS monitoring on the corporate information environment (Guedhami and Pittman 2008; El Ghoul et al. 2011; Bauer et al. 2020; Gallemore and Jacob 2020). Consequently, IRS monitoring could decrease banks' ability to extract informational rents and increase relationship borrowers' bargaining power. Therefore, if an increase in borrowers' bargaining power is the dominant channel through which IRS monitoring reduces bank loan costs, we predict that this effect will be more evident for borrowers with stronger lending relationships.

Thus, we formulate the following competing hypothesis ***H.2B***:

***H.2B The*** ***negative association of IRS monitoring with the cost of bank loans will be pronounced for loans granted to firms with stronger lending relationships.***

**3 Data and Methods**

**3. 1 Sample**

We source data on syndicated loans from the Thomson One Banker database. This database has provided comprehensive coverage of syndicated loans in the US since 1985 and has been used in several other studies (e.g., Isin 2018). It has comprehensive information on the characteristics of each loan facility (borrowing loan spread, amount, maturity, and covenants) and identifies the firm that receives each loan. This identification facilitates the matching of the firms from Thomson One Banker to Compustat to obtain firms' accounting and financial information. A firm could obtain multiple loan facilities in the same year, and we treat each loan facility as an individual observation.[[6]](#footnote-6) We also exclude loans to financial services firms (SIC codes 6000-6999) because these firms are subject to heavy regulation, and their borrowing terms may differ significantly from the rest of the firms in the sample. This matching process yields 15,858 loan facilities for 2,448 unique borrowing firms for the period from 1985 to 2017. At the firm-year level, we combine the available IRS tax enforcement data that starts in 1992 and the rest of the firm-level control variables to have a sample that comprises up to 7,054 firm-year observations for 1,335 unique firms for the period from 1993-2017.[[7]](#footnote-7) Table 1 provides the definitions and calculations of the variables we use in the analysis.

*Table 1*

**3. 2 Measures of IRS monitoring**

The primary IRS monitoring measure we use relies on data that we obtain from the Transactional Records Access Clearing House (TRAC). TRAC is a non-profit research institute associated with Syracuse University that collects data directly from the IRS. We source TRAC data on yearly IRS face-to-face corporate audit rates to use them as the main measure of IRS monitoring. These audit rates use information from the IRS about the corporate tax returns received and audits completed for eight size classes in terms of total assets each year.[[8]](#footnote-8) Thus, the IRS audit rates vary by size class and the calendar year. In particular, the variable *Audit rate* stands for the number of corporate audits completed in year *t* for a given IRS size class, divided by the number of the corporate tax returns received in the previous year (*t-1*) for the same size class. Therefore, the IRS audit rate captures the probability of a firm belonging to a specific size class that experienced a face-to-face IRS audit in a given year. Our identification strategy incorporates lagged IRS audit rates as the actual IRS audit rates become available to the public with a delay. The reason is that there is a lag between the time that a firm reports its tax returns to the IRS and the time that the IRS completes its investigations (Graham and Tucker 2006). Furthermore, using lagged values of the main variable of interest attenuates any concerns about endogeneity. We focus on the *Audit rate*measure of IRS monitoring because we are interested in capturing bank managers' view that a firm will experience an IRS audit in a given year.

To reinforce the reliability of our tax enforcement measure, the IRS Oversight annual reports submitted to the US Congress regularly refer to TRAC's statistics on corporate audit rates. Furthermore, IRS audit rates apply only to the US. This exclusivity eliminates issues stemming from institutional differences that plague cross-country data on tax enforcement (Hanlon et al. 2014). The credibility of the IRS audit rates as a measure of tax enforcement is evident in its wide use by the government and other academic studies (e.g., Guedhami and Pittman 2008; El Ghoul et al. 2011; Hoopes et al. 2012; Hanlon et al. 2014, Bauer et al. 2020).

**3.3 Measures of lending relationships**

We represent the strength of relationship lending between lenders and borrowing firms with two continuous measures of relationship intensity as in Bharath et al. (2011). We define the first measure as the volume of loans made by the same lead bank to the same borrowing firm during the last five years before the initiation of a new loan over the total volume of loans made to this borrower over that period (*RIA*).[[9]](#footnote-9) To this end, we use the following formula to calculate the relationship intensity for bank *j* lending to borrower *i*:

(1)

This measure ranges from zero to one. Values closer to one show that the borrowing firm has a stronger lending relationship with a particular lead bank. This measure is widely used by other studies (e.g., Bharath et al. 2011; Yildirim 2020; Delis et al. 2021). The second continuous measure we use is the ratio of the number of loans made by the same lead bank to a specific borrowing firm during the last five years over the total number of loans made to the same borrowing firm during the same period (*RIN*). Therefore, we measure the number-based relationship intensity for bank *j* lending to borrower *i* using the following specification:

(2)

Next, we use one dichotomous variable as the third proxy of relationship intensity. This variable equals one if the lead bank made more than one loan to the same firm in the last five years, while it equals zero otherwise (*REL DUM*). These two measures (*RIN* and *REL DUM*) are also widely used in the literature.

**3. 4 Regression specifications**

We test *H.1* with the following equation:

where is the natural logarithm of the *all-in-spread drawn* (AISD) that is the loan interest payment in basis points above LIBOR plus the annual fee for a loan facility that a firm obtains in year *t.*[[10]](#footnote-10) is the probability that a firm in a given size class will experience a face-to-face IRS audit in year *t-1*. We control for the following firm characteristics: size, leverage, profitability, tangibility, liquidity, risk, and the cash effective tax rate, all of which follow other empirical studies (e.g., Graham et al. 2008; Hasan et al. 2014). We also control for the listing status of each borrowing firm by using a binary variable that equals one if a firm is listed (*Listed*) in the stock market and zero otherwise. We also use a dummy variable to control for whether a borrowing firm is a member of the S&P 500 index. We further use a control variable for the credit rating of each borrowing firm. The dummy variable captures whether a firm has an investment-grade credit rating (*INV GRADE*) from Standard and Poor's (S&P). *INV GRADE* equals one if a borrowing firm has an equal to or above "BBB-" long-term credit rating from S&P, while it equals zero if the rating is below "BBB-" or if the firm is unrated. We use lagged information if the firm correlates from one year before the loan initiation to lessen concerns about endogeneity. We source the data for the firm-level variables from Compustat and Thomson One Banker. Details on the control variables are available in Table 1.

Two of these firm-level controls are essential to this study. The first is firm size, total, the natural log of total assets. This is because the IRS audit rates depend on the size class; hence, we must control for the size of the borrowing firms and to not confound the effect of IRS monitoring on the cost of bank loans with the effect of size. Furthermore, we also add the size class fixed effects to account for any potential systematic relationship between the costs of bank loans and borrowing firms belonging to a specific IRS-defined size class. The second important control in the regression model is the tax avoidance of the borrowing firms. We aim to investigate the effect of IRS monitoring on the cost of bank loans that stems from its role in reducing information asymmetry. Hence, not controlling for tax avoidance could confound this role with its role in reducing tax avoidance. The baseline model uses the cash-effective tax rate(*CASH ETR*) to measure tax avoidance. We measure *CASH ETR* as the ratio between cash taxes paid scaled by pre-tax book income minus special items. This measure gauges the impact of aggressive deferral and permanent tax strategies. As in Cen et al. (2017), we winsorize the cash-effective tax rate at zero and one, and we also multiply it by minus one (-1) for higher values to reflect higher tax avoidance.

Next, we add loan-level attributes to control for size and maturity as well as dummies for the type and purpose. Further, we add a dummy variable that equals one if a loan comprises covenants and zero otherwise. We also use a set of fixed effects that comprise the fixed effects for the year, industry (2-digit Standard Industrial Classification), lead bank, and the size class.

To test ***H.2A*** and ***H2.B***, we use the following equation:

The coefficient of interest in equation (4) comes from the interaction between IRS monitoring () and the three measures of lending relationships (*RIA*, *RIN*, *REL DUM*) that we explained in subsection 3.3.

**3. 5 Descriptive statistics and correlations**

Table 2 presents the lagged IRS audit rates by size class and time obtained from the TRAC database. We observe considerable variation across time and the different size classes in the same calendar year. For example, the lagged IRS audit rate for firms that fell within the largest size class in 2005 was 38.1%, while in 2017, it plummeted to a record low of 17.8%. Table 2 also shows the number of firm-year observations in each of the IRS size classes. The majority of our sample comprises large firms with assets beyond $250 million, as in other similar studies (Guedhami and Pittman 2008; Hoopes et al. 2012).

*Table 2*

Table 3 presents the summary statistics of the main explanatory variables of the empirical specifications. Loan characteristics show the average loan size and spread to be $522 million and 188 basis points, respectively. Furthermore, the mean loan maturity is around 3.4 years. These descriptive statistics align with Graham et al. (2008) and Hasan et al. (2014). Also, the mean values of the relationship intensity measure (0.470, 0.468, and 0.541) are consistent with those other studies. Table 4 presents the Pearson correlation coefficients among the main variables in our analysis. This preliminary evidence indicates that *Audit rate t-1* and *Loan spread* are negatively associated that supports ***H.1***. Altogether, we observe that *Audit rate t-1,* and the rest of the explanatory variables have a low correlation. This correlation attenuates any concerns about collinearity that could influence our estimations.

*Table 3 and Table 4*

**4 Empirical findings**

**4.1 Tests for Hypothesis H.1: The association between IRS monitoring and the cost of bank loans**

4.1.1 Baseline and 2SLS-IV estimations

Table 5 presents the baseline estimations regarding ***H.1***. Our models show a good fit with a 54% adjusted R2 on average. In model 1 of Table 5, we control only for the effect of *Audit rate t-1*on the cost of bank loans; while in model 2 of Table 5, we also account for loan characteristics; and in model 3, we add firm-level controls as well. The coefficients for *Audit rate t-1* are significant at the 1% level and negative (-0.021, -0.022, -0.020) in models 1, 2, and 3 of Table 5, respectively.

*Table 5*

Overall, these results support ***H.1*** that firms' bank loan spreads decrease when IRS monitoring is more stringent. Based on the average of the three coefficients of the lagged IRS audit rate in the first three models of Table 5 (-0.021), our findings, economically, indicate that one standard deviation increase in the lagged IRS audit rate (8.651) leads to an 8.84 basis points decrease in bank loan spreads (8.834=. Another way to assess the relevance of these findings is reflected by the interest savings based on the average loan size in our sample of $522 million, and the average time to maturity of around 3.4 years. As per our estimates, a one standard deviation increase in *Audit ratet-1* means around $1.49 million in interest savings (1.49=522\*0.00084\*3.4). Additionally, we show that larger firms with more tangible assets, higher profitability, lower risk, lower tax avoidance, less leverage, higher rating, and listed on the S&P enjoy lower borrowing costs, which is in line with similar studies (Graham et al. 2008; Bharath et al. 2011; Hasan et al. 2014; Huang et al. 2020). Furthermore, large loans with a shorter maturity are associated with lower loan spreads. These findings are consistent with Chava et al. (2008) who show that banks exposed to the risk of a longer maturity charge higher loan spreads as compensation.

The findings from the baseline models in Table 5 show that the lagged IRS audit rates and the cost of bank loans are negatively related. These results support ***H.1***. This support is due to the ability of stringent IRS monitoring to decrease information asymmetry.

The baseline models 1-3 in Table 5 assume that the IRS audit rate variable is exogenous to the cost of bank loans measure. We try to ease endogeneity concerns in our baseline models by using lagged IRS audit rates. To further address the potential endogeneity between the IRS audit rate and the cost of bank loans, we proceed with a two-stage least squares instrumental variable (2SLS-IV) estimation. In the first stage, we obtain predicted values of the IRS Audit rate t-1 using an OLS regression that comprises two instruments and all the control variables we employ in our baseline analysis. In the second stage, we replace the IRS audit rate variable with its predicted values that we obtain from the first stage.

For the first instrument, we follow the extant literature (Hoopes et al. 2012) and use the natural logarithm of the number of corporate tax returns in each asset size class filed in the previous year (Ln tax returns of size class t-2). By previous year we mean with respect to the Audit rate t-1. Hence, this instrument has a two-year lag from the dependent variable (i.e., the cost of bank loans). The IRS audit rate represents the number of actual corporate returns audited by the IRS in each firm size class in a given year divided by the number of corporate tax returns filed in each firm asset size class in the previous year. Consequently, IRS audit rates depend on fluctuations of corporate tax returns filed across time in the same firm size group. The numerator component (i.e., the number of corporate tax returns audited by the IRS) represents the IRS audit effort in each asset size class. In the case of a feedback effect, firms could, at least in theory, attempt to influence the IRS audit effort in their asset size class. Hence, the numerator component of the IRS audit measure, which represents the IRS audit effort, is more susceptible to endogeneity concerns. The denominator component (i.e., the number of corporate tax returns filed in each asset size class in the previous year), which we use as an instrument following Hoopes et al. (2012), is less susceptible to reverse causality because it is not likely that a firm will try to influence its IRS audit probability rate by not filing a tax return. Furthermore, since this instrument is not a measure of the IRS audit effort, it is unlikely that it would affect the cost of bank loans in a way other than its influence on the IRS audit rate for each asset size class (i.e., the exclusion restriction). We expect a negative and significant correlation of this instrument with the IRS audit rate in the first stage of the IV estimation.

We rely on the intuition that the IRS faces budget constraints each year for the second instrument. Such constraints mean that the IRS has limited audit resources to allocate to each asset size class each year. The IRS, in different periods, shifts its resources to specific target groups for auditing purposes (Scholz and Wood 1998; Bagchi 2016), such as, in our case, specific firm size classes. This action constraints the resources that the IRS could dedicate to monitoring and auditing firms in other asset-size groups. The shift of resources of the IRS to specific target groups for auditing purposes is also compatible with anecdotal evidence from the IRS operations. For example, the Transactional Records Access Clearinghouse (TRAC) states in 2008, '…By ordering its revenue agents to concentrate on the smaller corporations that normally take a lot less time to audit, the agency (i.e., the IRS) was able to push up the overall number of corporate audits...'. Based on the above discussion, we construct a second instrument by assigning to each borrowing firm in a given asset size class the lagged average IRS audit rate of the rest of the asset size classes (Average IRS audit rate of other size classes t-1). We expect this instrument to have a negative and significant relationship with the IRS audit rate of each asset size class. Furthermore, this instrument should, in principle, not directly affect the cost of bank loans for firms in a given asset size class since it does not represent the IRS audit rate for this specific group of firms (i.e., the exclusion restriction).

In model 4 of Table 5, we use the 2SLS-IV. The first-stage results show that the first instrument *(Ln tax returns of size class t-2)* has a significant association with the IRS audit rate at the 1% level and has the expected (i.e., negative) coefficient sign (see the lower part of model 4 in Table 5). Also, the first-stage findings show that the second instrument (*Average IRS audit rate of other size classes t-1*) displays a negative and significant relationship with the IRS audit rate at the 1% level (see the lower part of model 5 in Table 5). In model 6 of Table 5, we run 2SLS estimations using both instruments. We find that our two instruments continue to have a negative and significant association with the IRS audit rate at the 1% level. These results show that both instruments fulfil the inclusion criterion.

Furthermore, in model 6 of Table 5, the validity of the instruments is supported by the under-identification LM test (UIT), the weak identification Wald F-Test (WIT) using critical values from Stock and Yogo (2005), and the Hansen over-identification test of Hansen (OIT). The second stage results (models 4-6 of Table 5) show that the predicted values of the IRS audit rate (*Pred Audit rate t-1*) exert a negative and significant effect on the cost of bank loans at the 1% level. These findings further support ***H.1***.

**4.2 Tests for hypotheses H.2A and H.2B: The conditioning effect of lending relationships**

4.2.1 Main tests

We use three alternative proxies of lending relationships to test ***H.2A*** and ***H.2B***: *RIA*, *RIN*, and *REL DUM*. Table 6 depicts the results.

*Table 6*

In models 1, 3, and 5, we first run the baseline specification with all three variables. They have a negative but non-significant coefficient in these models. This finding is consistent with other studies (e.g., Hagendorff et al. 2021). A potential explanation is that the potential savings in screening and monitoring could be offset by the extraction of informational rents (Hasan et al. 2019). This is rational since both hold-up effects and savings in screening and monitoring costs coexist in lending relationships (Alexandre et al. 2014).

Models 2, 4, and 6 in Table 6 comprise the interactions between the three variables (*RIA*, *RIN*, and *REL DUM*) and *Audit rate t-1*. In models 2 and 4, we find that the interactions between *Audit rate* *t-1* and *RIA* and *RIN* have negative and significant coefficients at the 1% level. In the same models, the individual effect of *Audit rate t-1* on loan spreads is also negative and significant at the 1% level. We find similar results when using *REL DUM* in model 6 of Table 6.

These findings show that the negative association between IRS monitoring and loan spreads becomes pronounced for firms with strong lending relationships. These findings are consistent with ***H.2B***.

The positive and significant individual effect of the lending relationship variables (*RIA*, *RIN*, and *REL DUM)* denotes that when IRS monitoring is weak, banks are more able to extract informational rents from their relationships with borrowers. However, as IRS monitoring becomes stringent, relationship banks' informational advantage *vis-à-vis* other providers of external financing diminishes. Consequently, banks are less able to hold-up their relationship borrowers as the negative interaction between the lending relationships variables and the IRS monitoring proxy indicates.

To visually demonstrate the findings that support hypothesis *H.2B*, we offer two interaction plots of *RIA* and *RIN* with *Audit rate* *t-1*. These interaction plots in Figures 1 and 2 illustrate that the negative association between IRS monitoring and loan spreads becomes more apparent when lending relationships intensify.

*Figure 1 and Figure 2*

The empirical evidence supporting ***H.2B*** is consistent with studies that identify the factors that decrease information asymmetries and improve firms’ information environment and therefore increase borrowers' bargaining power and decrease banks' ability to extract informational rents from their lending relationships (Schenone 2010; Cahn et al. 2021; Saidi and Zaldokas 2021). In our context, the ability of IRS monitoring to decrease information asymmetry could weaken the informational advantage of incumbent banks and render it more credible that relationship borrowers could access alternative providers of external financing (Guedhami and Pittman 2008; El Ghoul et al. 2011; Bauer et al. 2020; Gallemore and Jacob 2020). Hence, banks may perceive that their relationship borrowers have increased bargaining power in the presence of more stringent IRS monitoring.

4.2.2 The role of credible access to the public markets for external financing

Next, we investigate the type of borrowers for which the findings for ***H.2B*** are more evident. The public markets for external financing rely more strongly than the private lending market on external monitoring from entities such as the IRS. Investors in the public market have weaker monitoring incentives than banks because they are usually more widely dispersed (Diamond 1984; Boot and Thakor 2009; Bharath and Hertzel 2019). Furthermore, the public markets depend more strongly than banks on high-quality publicly available hard information (Liberti and Petersen 2019). Banks could supplement this information with inside (private) information on the borrowing firm that public investors do not have access to (Fama 1985; Dass and Massa 2011). Thus, the public markets are likely to more highly value the ability of the IRS to decrease information asymmetry than private lenders. Therefore, IRS monitoring might be more important for decreasing the informational advantage, and hence the capacity to extract rents from the lending relationships of incumbent banks *vis-à-vis* the public markets than other private lenders.

We use three variables to represent a firm's ability to access the public markets for external financing. The first variable indicates if a firm is listed in the stock market (*Listed*). The second is the variable that captures if a firm is a member of the prestigious S&P 500 index (*S&P500*). The third variable denotes if a firm has an investment-grade credit rating (*INV GRADE*). Then, we use models that comprise triple interaction terms between these three proxies and *Audit rate* *t-1* and *RIA*, *RIN,* and *REL DUM*.

*Table 7*

Table 7 depicts the findings. In Panel A of Table 7, we run models that estimate the effect of the triple interaction term on the cost of bank loans. Panel A shows that the triple interaction is negative and significant across all models (1-3), at least at the 10% level. In Panel B of Table 7, we repeat this exercise using the *S&P500* dichotomous variable as one of the regressors in the triple interaction. We observe similar findings in models 1-3 where we use the three alternative measures of lending relationships. The triple interactions are negative and significant, at least at the 5% level. Lastly, we run similar estimations using *INV GRADE*. Model 3 in Panel C shows that the triple interactions are negative and significant at the 1% level like our earlier findings.

These findings support our theoretical prediction that under more stringent IRS monitoring, the cost of bank loans decreases more for relationship borrowers that have credible access to the public markets of external financing. By decreasing information asymmetry, IRS monitoring reduces incumbent banks’ informational advantage and facilitates less costly access to the public markets (Allen and Gottesman 2006; Santos and Winton 2008; Hale and Santos 2009; Saunders and Steffen 2011). Therefore, the borrowers' bargaining power *vis-à-vis* banks could increase. As a consequence, the ability of incumbent banks to extract informational rents from lending relationships diminishes.

4.2.3 Split-sample analysis based on the strength of lending relationships

Next, we perform a split sample analysis based on the median of *RIA* and *RIN*. This exercise provides further insights into the conditioning effect of lending relationships on the association between IRS monitoring and the cost of bank loans. The results are in Table 8. We show that the interactions between *RIA* and *RIN* and *Audit rate* *t-1* are negative and significant for both subsamples (see models 1-2 of Panel A and 3-4 of panel B of Table 8). These findings support ***H.2B***.

*Table 8*

The different results for the two subsamples reflect that the individual effect of *Audit rate* *t-1* on loan spreads is negative and significant only for low lending relationships (compare models 1 and 2 with models 3 and 4 in Panel A of Table 8). We interpret this result in the following way: When lending relationships are weaker, the ability of the IRS monitoring to decrease information asymmetry could be of some value to the banks' lending. Weaker lending relationships mean that banks have not yet collected a high level of private information on borrowers. Therefore, IRS monitoring could be helpful for the screening and monitoring of borrowers at this stage. For example, the quality of borrowers' information environment, such as the financial reporting transparency that IRS monitoring enhances, could be more useful when banks hold less proprietary information and are less familiar with borrowers (Bharath et al. 2008; Berger et al. 2017).

However, as lending relationships strengthen, the negative association between *Audit rate* *t-1* and loan spreads becomes more evident through its negative and significant interaction with *RIA* and *RIN*. This finding indicates that at a higher level of lending relationships, IRS monitoring increases borrowers' bargaining power and restrains banks' ability to extract rents from the private information they accumulate on borrowers. Indeed, for the high lending relationship subsample (see models 1 and 2 of Panel B of Table 8), the negative association of IRS monitoring with loan spreads occurs only via the negative and significant interaction with the lending relationship variables (i.e., ***H.2B***). The insignificant coefficient for *Audit rate* *t-1* in the high lending relationship subsample further indicates that in this context, the low information asymmetry stemming from past interactions renders IRS monitoring less beneficial for the relationship banks' screening and monitoring operations.

Another difference between the lower and higher lending relationship subsamples is that the coefficients for *RIA* and *RIN* are different; the one for the first is positive and significant but the one for the second is not significant. A potential explanation is the confluence of the distinct hold-up and the pass-through savings effects of screening and monitoring that coexist in lending relationships (Alexandre et al. 2014). After gaining a new borrower, banks tend to increase loan prices that is a behavior consistent with the hold-up effect (Ioannidou and Ongena 2010). When lending relationships intensify to a high level, the information asymmetry between borrowers and banks reaches a minimum. Consequently, substantial savings in screening and monitoring could offset the hold-up effect.

We continue the split sample analysis with models that comprise the triple interaction terms between *Audit rate t-1*; *RIA* and *RIN*; and *Listed*, *S&P500,* and *INV GRADE*. The results from these tests are available in Table 9.

*Table 9*

For the high lending relationships subsample, we find negative and significant triple interaction terms between *Audit rate t-1*, *RIA* and *RIN*, and the *Listed* and *S&P500* dummies (see models 3 and 4 in Panels A and B of Table 9). The interaction term between the lending relationship measures and IRS monitoring in the same models loses significance. These findings show that credible access to external public financing facilitates the negative association between IRS monitoring and the cost of bank loans for firms that display strong lending relationships with their banks (i.e., ***H.2B***).

The results for the low lending relationship subsample show that the negative interactions between *Audit rate t-1* and *RIA* and *RIN* remain negative and significant. However, the triple interaction terms with *Listed*, *S&P500,* and *INV GRADE* are not significantly different from zero. These findings show that for the low lending relationship subsample, the negative interaction between IRS monitoring and lending relationships (i.e., ***H.2B***) is apparent for both bank-dependent firms and firms with credible access to external public financing.

Firms in the high lending relationship subsample rely mainly on their relationship banks to access bank credit. The informational advantage of these relationship banks *vis-à-vis* other private lenders is strong. Hence, the ability of IRS monitoring to decrease information asymmetry might not be able to adequately erode incumbent banks' informational advantage to make losing relationship borrowers to outside banks more plausible.

**5 Summary of further analyses and additional robustness tests**

We perform further analyses and robustness tests that we tabulate and discuss in more detail in the Internet Appendix.

We investigate the association between IRS monitoring and some non-price loan contract terms. The results are in line with the main analysis. We provide evidence that IRS monitoring negatively affects the probability that a loan will contain covenants. We also show that the negative association between IRS monitoring and covenant presence becomes more pronounced for firms with more intense lending relationships. These findings support hypotheses ***H.1*** and ***H.2B***, respectively.

The probability of an IRS audit, which is our main IRS monitoring measure, hinges on the size class, as defined by the IRS, to which it belongs. We carry out several additional tests to ensure that our findings are not driven by firm size. We run models that comprise the squared and cubed values of a firm’s size. Furthermore, we perform estimations that use the natural log of sales and equity as alternative measures of size. To account for potential time trends in each size class (e.g., larger firms may have become less risky over time), we also run estimations with time trends for each size class.

To further mitigate concerns about our main IRS monitoring proxy, we use alternative IRS monitoring proxies, as in Guedhami and Pittman (2008). For example, we use IRS staffing levels as a monitoring proxy. Some research has acknowledged that staffing is crucial in strengthening IRS tax enforcement (Weisman 2004; Rapperort 2017). We also use data on IRS referrals, prosecutions, and penalties to capture further aspects of IRS monitoring. In another test, we introduce a geographic source of variation in IRS monitoring to our models. Kubick et al. (2017) show that IRS monitoring is more stringent when a firm is closer to an IRS office (territory manager office. We find that the negative association between IRS monitoring and loan spreads is more evident for borrowers in states with more IRS offices.

In the main analysis, we control for tax avoidance using the cash-effective tax rate (*Cash ETR*)*.* In the Internet Appendix, we use several other tax avoidance measures as control variables. We continue to find a negative effect of IRS monitoring on loan pricing that is incremental to the effect of tax avoidance and consistent with the monitoring and informational role of the IRS in financial markets.

In another exercise, we reestimate the baseline models using alternative ways to cluster the standard errors. We estimate models in which we cluster the standard errors at the size class and year levels because *Audit rate t-1* displays variation in both cases. We also depict the results from specifications where we cluster the standard by borrowing firms and banks because the lending relationship variables are based on firm-bank pairs.

Finally, we perform several other tests. These comprise the estimation of models that exclude the loans granted to firms belonging to the largest IRS-defined size class: models that use the contemporaneous IRS audit rate, models that control for the syndicate size, and models that control for the state-level index that reflects the time-variant, business tax climate. In all these tests, we continue to find a negative and significant association between IRS monitoring and the cost of bank loans.

**6 Conclusion**

This study sheds some light on the relationship between IRS monitoring and the cost of bank loans in the US syndicated loan market. We hypothesize that the IRS has a valuable role in external monitoring that alleviates information asymmetry that can lower loan prices. Our findings provide strong empirical support for this conjecture. We show that IRS monitoring has a negative and significant effect on the cost of bank loans. Furthermore, we show that this association is economically significant. This finding holds in a series of tests, such as instrumental variable estimations that mitigate the concerns for endogeneity and models that use alternative IRS monitoring proxies.

We also investigate potential mechanisms through which IRS monitoring reduces the cost of bank loans. We show that the negative association of IRS monitoring with the cost of bank loans is more evident for loans granted to firms with stronger lending relationships, especially when these borrowers have credible access to the public markets of extremal financing. These results are consistent with the argument that the ability of IRS monitoring to decrease information asymmetry erodes the informational advantage that banks acquire through lending relationships and renders the markets for external financing more contestable. Therefore, IRS monitoring increases borrowers' bargaining power and restricts banks' ability to extract rents from their lending relationships. The finding that these effects are more apparent for borrowers with credible access to the public markets underlines the vital importance of external monitors for investors in these markets.

This study is useful from a theoretical standpoint because it provides a novel insight into how IRS monitoring could drive the reduction in the cost of corporate financing through the banking system. From a public policy perspective, this study is timely and highlights the usefulness of the IRS to the US economy. Except for its primary function as a tax collection agency, the IRS exerts a positive spillover to the US economy in the form of lower bank loan costs. This is an important finding because bank loans are the most crucial source of external financing for US corporations. Therefore, this study informs from this perspective the policy debate about the future of the IRS.

**Declarations**

**Funding and/or Conflicts of interests/Competing interests**

The authors have no conflicts of interest to declare that are relevant to the content of this article.

**References**

Alexandre, H., Bouaiss, K., and Refait-Alexandre, C. 2014. Banking relationships and syndicated loans during the 2008 financial crisis. *Journal of Financial Services Research*, *46*(1), 99-113.

Allen, L., and Gottesman, A. 2006. The informational efficiency of the equity market as compared to the syndicated bank loan market. *Journal of Financial Services Research*, *30*(1), 5-42.

Bagchi, S. 2016. The political economy of tax enforcement: a look at the Internal Revenue Service from 1978 to 2010. *Journal of Public Policy*, *36*(3), 335-380.

Bannier, C. E., and Hirsch, C. W. 2010. The economic function of credit rating agencies–What does the watchlist tell us? *Journal of Banking & Finance*, *34*(12), 3037-3049.

Bauer, A. M., Fang, X., and Pittman, J. 2020. The importance of IRS enforcement to stock price crash risk: The role of CEO power and incentives. *The Accounting Review*. Forthcoming.

Berger, P.G., Minnis, M. and Sutherland, A. 2017. Commercial lending concentration and bank expertise: Evidence from borrower financial statements. *Journal of Accounting and Economics*, *64*(2-3), 253-277.

Bharath, S. T., Sunder, J., and Sunder, S. V. 2008. Accounting quality and debt contracting. *The Accounting Review*, *83*(1), 1-28.

Bharath, S., Dahiya, S., Saunders, A., and Srinivasan, A. 2011. Lending relationships and loan contract terms. *The Review of Financial Studies*, *24*(4), 1141-1203.

Bharath, S.T. and Hertzel, M. 2019. External governance and debt structure. *The Review of Financial Studies*, *32*(9), 3335-3365.

Boone, A.L. and White, J.T. 2015. The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics*, *117*(3), 508-533.

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

Boot, A., Thakor, A. V. 2009. The Accelerating Integration of Banks and Markets and its Implications for Regulation. Oxford Handbook of Banking, Oxford University Press.

Boot, A., and Thakor, A. V. 1994. Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review*, 899-920.

Booth, J. R. 1992. Contract costs, bank loans, and the cross-monitoring hypothesis. *Journal of Financial Economics*, *31*(1), 25-41.

Bushman, R. M., Williams, C. D., and Wittenberg‐Moerman, R. 2017. The informational role of the media in private lending. *Journal of Accounting Research*, *55*(1), 115-152.

Cahn, C., Girotti, M., and Salvadè, F. 2021. Credit ratings and the hold-up problem in the loan market. Working paper.

Cen, L., Dasgupta, S., Elkamhi, R., and Pungaliya, R. S. 2016. Reputation and loan contract terms: The role of principal customers. *Review of Finance*, *20*(2), 501-533.

Cen, L., Maydew, E. L., Zhang, L., and Zuo, L. 2017. Customer–supplier relationships and corporate tax avoidance. *Journal of Financial Economics*, *123*(2), 377-394.

Chakraborty, I., Goldstein, I., and MacKinlay, A. 2018. Housing price booms and crowding-out effects in bank lending. *The Review of Financial Studies*, *31*(7), 2806-2853.

Chava, S., and Roberts, R. 2008. How does financing impact investment? The role of debt covenants. *The Journal of Finance*, *63*, 2085-2121.

Chen, J., Gong, D. and Muckley, C., 2020. Stock market illiquidity, bargaining power and the cost of borrowing. *Journal of Empirical Finance*, *58*, 181-206.

Chen, S., Chen, X., Cheng, Q., and Shevlin, T. 2010. Are family firms more tax aggressive than non-family firms? *Journal of Financial Economics*, *95*(1), 41-61.

Chen, T., Harford, J., and Lin, C. 2015. Do analysts matter for governance? Evidence from natural experiments. *Journal of Financial Economics*, *115*(2), 383-410.

Contessi, S., Li, L. and Russ, K. 2013. Bank vs. bond financing over the business cycle. *Economic Synopses*, *31*, 1-3.

Coyne, J., and Stice, D. 2018. Do banks care about analysts' forecasts when designing loan contracts? *Journal of Business Finance & Accounting*, *45*(5-6), 625-650.

Dass, N. and Massa, M. 2011. The impact of a strong bank-firm relationship on the borrowing firm. *The Review of Financial Studies*, *24*(4), 1204-1260.

Degryse, H., and Ongena, S. 2005. Distance, lending relationships, and competition. *The Journal of Finance*, *60*(1), 231-266.

Delis, M., Kim, S., Politsidis, P., and Wu, E. 2021. Regulators vs. markets: Are lending terms influenced by different perceptions of bank risk? *Journal of Banking & Finance*, *122*, 105990.

Desai, A., and Dharmapala, D. 2009. Corporate tax avoidance and firm value. *The Review of Economics and Statistics*, *91*, 537-546.

Desai, A., Dyck, A., and Zingales, L. 2007. Theft and taxes. *Journal of Financial Economics*, *84*, 591-623.

Desai, M.A. and Dharmapala, D. 2006. Corporate tax avoidance and high-powered incentives. *Journal of Financial Economics*, *79*(1), 145-179.

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

Dyck, A., Morse, A., and Zingales, L. 2010. Who blows the whistle on corporate fraud? *The Journal of Finance*, *65*, 2213-2253.

El Ghoul, S., Guedhami, O., and Pittman, J. 2011. The role of IRS monitoring in equity pricing in public firms. *Contemporary Accounting Research*, *28*, 643-674.

Fama, E.F. 1985. What's different about banks? *Journal of Monetary Economics*, *15*(1), 29-39.

Florou, A. and Kosi, U., 2015. Does mandatory IFRS adoption facilitate debt financing? *Review of Accounting Studies*, *20*(4), 1407-1456.

Gallemore, J., and Jacob, M., 2020. Corporate tax enforcement externalities and the banking sector. *Journal of Accounting Research*, *58*(5), 1117-1159.

Graham, J., and Tucker, A. 2006. Tax shelters and corporate debt policy. *Journal of Financial Economics*, *81*(3), 563-594.

Graham, R., Li, S., and Qiu, J., 2008. Corporate misreporting and bank loan contracting. *Journal of Financial Economics*, *89*, 44-61.

Guedhami, O., and Pittman, J. 2008. The importance of IRS monitoring to debt pricing in private firms. *Journal of Financial Economics*, *90*, 38-58.

Gustafson, M., Ivanov, I., and Meisenzahl, R. 2020. Bank monitoring: Evidence from syndicated loans. *Available at SSRN 2831455*.

Hagendorff, J., Lim, S., and Nguyen, D. 2021. Lender trust and bank loan contracts. *Available at SSRN 3183155*.

Hale, G., and Santos, J. 2009. Do banks price their informational monopoly? *Journal of Financial Economics*, *93*(2), 185-206.

Hanlon, M., Hoopes, L., and Shroff, N. 2014. The effect of tax authority monitoring and enforcement on financial reporting quality. *The Journal of the American Taxation Association*, *36*, 137-170.

Hasan, I., Hoi, C. K., Wu, Q., and Zhang, H. 2017. Social capital and debt contracting: Evidence from bank loans and public bonds. *Journal of Financial and Quantitative Analysis*, *52*(3), 1017-1047.

Hasan, I., Hoi, S., 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*, 109-130.

Hasan, I., Ramirez, G., and Zhang, G. 2019. Lock‐In Effects in Relationship Lending: Evidence from DIP Loans. *Journal of Money, Credit and Banking*, *51*(4), 1021-1043.

Hill, M. D., Kubick, T. R., Lockhart, G. B., and Wan, H. 2013. The effectiveness and valuation of political tax minimization. *Journal of Banking & Finance*, *37*(8), 2836-2849.

Hoopes, L., Mescall, D., and Pittman, J. A. 2012. Do IRS audits deter corporate tax avoidance? *The Accounting Review*, *87*, 1603-1639.

Huang, Y., Hasan, I., Huang, Y., and Lin, C. 2020. Political uncertainty and Bank Loan Contracts: Does government quality matter? *Journal of Financial Services Research*, 1-29.

Ioannidou, V., and Ongena, S. 2010. “Time for a change”: loan conditions and bank behavior when firms switch banks. *The Journal of Finance*, *65*(5), 1847-1877.

Isin, A. A. 2018. Tax avoidance and cost of debt: The case for loan-specific risk mitigation and public debt financing. *Journal of Corporate Finance*, *49*, 344-378.

Ivashina, V. 2009. Asymmetric information effects on loan spreads. *Journal of Financial Economics*, *92*(2), 300-319.

Jia, Y., and Gao, X. 2021. Is managerial rent extraction associated with tax aggressiveness? Evidence from informed insider trading. *Review of Quantitative Finance and Accounting*, *56*(2), 423-452.

Kim, C., and Zhang, L. 2016. Corporate political connections and tax aggressiveness. *Contemporary Accounting Research*, *33*(1), 78-114.

Kim, J.B., Li, Y. and Zhang, L. 2011. Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics*, *100*(3), 639-662.

Kubick, T.R., Lockhart, G.B., Mills, L.F. and Robinson, J.R. 2017. IRS and corporate taxpayer effects of geographic proximity. *Journal of Accounting and Economics*, *63*(2), 428-453.

Leuz, C., Nanda, D. and Wysocki, P.D. 2003. Earnings management and investor protection: an international comparison. *Journal of Financial Economics*, *69*(3), 505-527.

Liberti, J.M. and Petersen, M.A. 2019. Information: Hard and soft. *Review of Corporate Finance Studies*, *8*(1), 1-41.

Lim, Y. 2011. Tax avoidance, cost of debt and shareholder activism: Evidence from Korea. *Journal of Banking & Finance*, *35*(2), 456-470.

Lin, C. Y., Tsai, W. C., and Hasan, I. 2018. Private benefits of control and bank loan contracts. *Journal of Corporate Finance*, *49*, 324-343.

Mattes, J., Steffen, S., and Wahrenburg, M. 2013. Do information rents in loan spreads persist over the business cycles? *Journal of Financial Services Research*, *43*(2), 175-195.

Mazumdar, S.C. and Sengupta, P. 2005. Disclosure and the loan spread on private debt. *Financial Analysts Journal*, *61*(3), 83-95.

Mironov, M. 2013. Taxes, theft, and firm performance. *The Journal of Finance*, *68*(4), 1441-1472.

Nessa, M., Schwab, C. M., Stomberg, B., and Towery, E. M., 2020. How do IRS resources affect the corporate audit process? *The Accounting Review*, 95(2), 311-338.

Ni, X., and Yin, S. 2018. Shareholder litigation rights and the cost of debt: Evidence from derivative lawsuits. *Journal of Corporate Finance*, *48*, 169-186.

Petersen, M., and Rajan, R. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, *49*(1), 3-37.

Prilmeier, R. 2017. Why do loans contain covenants? Evidence from lending relationships. *Journal of Financial Economics*, *123*(3), 558-579.

ProPublica, 2019. Gutting the IRS: Who wins when crucial agency is defunded. Available at [https://www.propublica.org/series/gutting-the-irs#](https://www.propublica.org/series/gutting-the-irs)

Rajan, R. (1992). Insiders and outsiders: The choice between informed and arm's‐length debt. *The Journal of Finance*, *47*(4), 1367-1400.

Rapperort, A. 2017, March 2. Under Trump, an Already Depleted I.R.S. Could Face Deep Cuts. *The New York Times.* Available at*:* <http://www.latimes.com/politics/washington/la-na-essential-washington-updates-trump-budget-to-slash-irs-funding-1489665882-htmlstory.html>

Saidi, F. and Žaldokas, A. 2021. How does firms’ innovation disclosure affect their banking relationships? *Management Science*, *67*(2), 742-768.

Santos, J., and Winton, A. 2008. Bank loans, bonds, and information monopolies across the business cycle. *The Journal of Finance*, *63*(3), 1315-1359.

Saunders, A., and Steffen, S. 2011. The costs of being private: Evidence from the loan market. *The Review of Financial Studies*, *24*(12), 4091-4122.

Schenone, C. 2010. Lending relationships and information rents: Do banks exploit their information advantages? *The Review of Financial Studies*, *23*(3), 1149-1199.

Scholz, T., and Wood, D. 1998. Controlling the IRS: Principals, principles, and public administration. *American Journal of Political Science*, 141-162.

Sharpe, S. 1990. Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance*, *45*(4), 1069-1087.

Shevlin, T. J., Urcan, O., and Vasvari, F. P. 2013. Corporate tax avoidance and public debt costs. Working paper, Available at SSRN: <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2228601>

Shevlin, T., Urcan, O. and Vasvari, F.P. 2020. Corporate tax avoidance and debt costs. *Journal of the American Taxation Association*, *42*(2), pp.117-143.

Stock, J.H. and Yogo, M. 2005. Testing for weak instruments in linear IV regression. Identification and inference for econometric models: Essays in honor of Thomas Rothenberg, chap. 5, 80-108.

Sufi, A. 2007. Information asymmetry and financing arrangements: Evidence from syndicated loans. *The Journal of Finance*, *62*(2), 629-668.

Transactional Records Access Clearing House. 2019. Millionaires and corporate giants escaped IRS audits in FY 2018. Available at <https://trac.syr.edu/tracirs/latest/549/>

Weisman, J. 2004, March 20. IRS Opting Not to Go After Many Scofflaws. *The Washington Post*. Available at [https://www.washingtonpost.com/archive/politics/2004/03/20/irs-opting-not-to-go-after-many-scofflaws/acf4ceef-1171-44e4-b7e7 ce3406fef505/?utm\_term=.dcf0edf342d2](https://www.washingtonpost.com/archive/politics/2004/03/20/irs-opting-not-to-go-after-many-scofflaws/acf4ceef-1171-44e4-b7e7%20ce3406fef505/?utm_term=.dcf0edf342d2)

Wilson, J. 2009. An examination of corporate tax shelter participants. *The Accounting Review*, *84*, 969-999.

Yildirim, A. 2020. The effect of relationship banking on firm efficiency and default risk. *Journal of Corporate Finance*, *65*, 101500.

**List of Tables**

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| --- | --- | --- |
| **Table 1** Variable definitions, measurements, and sources | |  |
| **Panel A.** Dependent variable and main explanatory variables | |  |
| IRS monitoring | Definitions | Source |
| *Audit rate t-1* | Probability of a firm facing an IRS audit in year t-1. This measure is calculated as the number of audits of corporate tax returns completed in the IRS’s ﬁscal year t-1 for a given IRS size class over the number of corporate tax returns received in the t-2 calendar year for the same IRS size class. | TRAC |
| Firm characteristics |  |  |
| *Firm size t-1* | The natural logarithm of total assets in year t-1 | COMPUSTAT |
| *ROA t-1* | Net operating income divided by total assets in year t-1 | COMPUSTAT |
| *Liquidity t-1* | Current assets divided by total assets in year t-1 | COMPUSTAT |
| *Leverage t-1* | Long-term debt divided by total assets in year t-1 | COMPUSTAT |
| *Tangibility t-1* | Net property, plant, and equity divided by total assets in year t-1 | COMPUSTAT |
| *Cash ETR t-1* | The ratio of cash taxes paid (Compustat: TXPD) to pre-tax income adjusted for special items [Compustat: (TXPD)/(PI − SPI)]. The measure is winsorized at the [0,1] interval. It also excludes observations with a negative or zero (PI − SPI), i.e., the effective tax rate is set as missing when the denominator is zero or negative. This measure is multiplied by (−1) so that an increase in the measure reflects increased tax avoidance. | COMPUSTAT |
| *Altman's z-score t-1* | Altman's z-score (1968) = (1.2\*Working Capital t-1 + 1.4 \*Retained Earnings t-1 +3.3\*EBIT t-1 + 0.999\*Sales t-1)/Total Assets t-1) | COMPUSTAT |
| *Listed t-1* | Dummy variable that equals one if borrowing firms trade on the NASDAQ, NYSE, or the AMEX stock exchanges and zero otherwise. | COMPUSTAT |
| *S&P500 t-1* | Dummy variable that equals one if borrowing firms are listed on the S&P 500 stock market index and zero otherwise. | COMPUSTAT |
| *INV Grade t-1* | A dummy variable that equals one if a borrowing firm has an equal to or above "BBB-" long-term credit rating by S&P while it equals zero if the rating is below "BBB-" or if the firm is unrated. | Thomson One Banker |
| Loan characteristics |  |  |
| *Loan spread t (basis points)* | The “all-in-spread drawn” (AISD) is the loan interest payment in basis points over the LIBOR plus the annual fee for a loan facility that a firm obtains in year t. | Thomson One Banker |
| *Loan size t ($ Millions)* | Total dollar amount of a loan facility obtained by a firm in year t. | Thomson One Banker |
| *Loan maturity t (year)* | Number of years to maturity of a loan facility obtained by a firm in year t. | Thomson One Banker |
| *Covenant t*  *Loan purpose dummy t* | Equals one if a loan facility obtained by a firm in year t has covenants and zero otherwise.  A group of dummy variables that capture the loan’s primary purpose. | Thomson One Banker  Thomson One Banker |
| *Loan type dummy t* | A group of dummy variables capturing loan type. | Thomson One Banker |
| Lending relationships measures |  |  |
| *RIA t* | The ratio of the dollar value of loans credited by the same lead bank to the same borrowing firm in the last five years before the initiation of a new loan over the total dollar value of all loans granted to this borrower over this period. | Thomson One Banker |
| *RIN t* | The ratio of the number of loans credited by the same lead bank to a specific borrowing firm during the last five years before the initiation of a new loan over the total number of loans granted in the same borrowing firm during the same period. | Thomson One Banker |
| *REL DUM t* | Dummy variable that equals one if a firm has been granted a loan by the same lead bank in the last five years before the initiation of a new loan, while it equals zero otherwise. | Thomson One Banker |

**Table 2.** IRS face-to-face audit rates of corporate income tax returns and sample distribution

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **IRS lagged audit rates across time and size** | | | | | | | | | | | | | | | | | | | | | | | | | | **Sample Distribution** |
| **Asset class** | **1993** | **1994** | **1995** | **1996** | **1997** | **1998** | **1999** | **2000** | **2001** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **Total** |
| >$250 Million | 54.6 | 55.5 | 54.7 | 50.9 | 48.4 | 45.9 | 37.3 | 34.6 | 30.5 | 31.4 | 33.7 | 29 | 38.1 | 42.6 | 34.2 | 26.3 | 26.9 | 25 | 24.3 | 27 | 28.5 | 32.3 | 24.7 | 19.9 | 17.8 | **6369** |
| $100-250 Million | 31.3 | 32.3 | 30.6 | 27.8 | 26.8 | 22.5 | 19 | 18.5 | 16.9 | 17.1 | 15.5 | 12.2 | 15.9 | 16.7 | 13.7 | 11.5 | 12.6 | 13.3 | 14.4 | 16.4 | 22.5 | 18.8 | 12.4 | 13.4 | 10.4 | **468** |
| $50-100 Million | 28.5 | 25.4 | 24.3 | 21.5 | 20.8 | 19.2 | 17.5 | 16 | 14.1 | 11.9 | 10.3 | 9.4 | 12.1 | 15.5 | 13.4 | 10.9 | 11.4 | 14 | 15.9 | 18.6 | 20.4 | 15 | 10.8 | 10.7 | 9.9 | **152** |
| $10-50 Million | 23.2 | 23.3 | 22.2 | 19.6 | 19.7 | 20 | 17.7 | 14.7 | 11.4 | 9.3 | 7.5 | 5.9 | 8.8 | 11.4 | 14 | 14.7 | 11.6 | 9.9 | 13.2 | 13.1 | 10.1 | 6.6 | 5.9 | 5.3 | 4.4 | **61** |
| $5-10 Million | 18.8 | 19.3 | 15.7 | 14.7 | 13.9 | 16 | 13.4 | 10.1 | 6.8 | 5.1 | 4.5 | 3.2 | 1.9 | 2.4 | 3.3 | 2.9 | 3 | 2.6 | 2.8 | 2.5 | 2.4 | 1.7 | 1.7 | 1.3 | 1.4 | **1** |
| $1-5 Million | 9.9 | 9.6 | 7 | 6 | 6.6 | 7.7 | 6.4 | 4.9 | 2.9 | 2 | 2 | 1.5 | 0.6 | 0.9 | 1.1 | 1.6 | 1.9 | 1.8 | 1.7 | 1.9 | 2 | 1.3 | 1.1 | 1 | 0.9 | **2** |
| $0,25- 1 Million | 4 | 4 | 2.4 | 2.1 | 2.7 | 3.5 | 2.5 | 1.7 | 1.1 | 0.8 | 0.7 | 0.6 | 0.3 | 0.9 | 0.9 | 1.3 | 1.3 | 1.3 | 1.3 | 1.6 | 1.6 | 1.2 | 1.2 | 1.1 | 1 | **1** |
| **Total** | **109** | **141** | **14** | **40** | **119** | **146** | **104** | **675** | **619** | **440** | **406** | **464** | **424** | **355** | **387** | **250** | **136** | **250** | **375** | **268** | **341** | **296** | **320** | **311** | **64** | **7054** |

**Table 3** Descriptive statistics. The table presents the descriptive statistics for the 7,054 firm-year observations over the period from 1993-2017 used in our baseline regression analysis. Table 1 provides full details on the definitions and calculation for all variables.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Count** | **Mean** | **Standard Deviation** | **25th percentile** | **50th percentile** | **75th percentile** |
| *Audit rate t-1* | 7054 | 30.554 | 8.651 | 25.000 | 30.500 | 34.600 |
| **Firm characteristics** | |  |  |  |  |  |
| *Firm size t-1* | 7054 | 7.647 | 1.643 | 6.507 | 7.649 | 8.790 |
| *ROA t-1* | 7054 | 0.022 | 0.030 | 0.012 | 0.022 | 0.034 |
| *Liquidity t-1* | 7054 | 1.762 | 1.674 | 1.025 | 1.473 | 2.123 |
| *Leverage t-1* | 7054 | 0.527 | 0.233 | 0.385 | 0.504 | 0.636 |
| *Tangibility t-1* | 7054 | 0.669 | 0.450 | 0.322 | 0.611 | 0.948 |
| *Cash ETR t-1* | 7054 | 0.179 | 0.174 | 0.003 | 0.160 | 0.290 |
| *Altman's z-score t-1* | 7054 | 1.061 | 1.526 | 0.419 | 0.967 | 1.673 |
| *Listed t-1* | 7054 | 0.799 | 0.401 | 1 | 1 | 1 |
| *S&P500 t-1* | 7054 | 0.367 | 0.482 | 0 | 0 | 1 |
| *INV Grade t-1* | 7054 | 0.056 | 0.229 | 0 | 0 | 0 |
| **Loan characteristics** | |  |  |  |  |  |
| *Loan spread t (basis points)* | 7054 | 188 | 142 | 87 | 150 | 250 |
| *Loan size t ($ Millions)* | 7054 | 522 | 1010 | 100 | 250 | 570 |
| *Loan maturity t (year)* | 7054 | 3.4 | 1.9 | 3.0 | 5.0 | 5.0 |
| **Lending relationships measures** | | | |  |  |  |
| *RIA t* | 7054 | 0.470 | 0.457 | 0 | 0.413 | 1 |
| *RIN t* | 7054 | 0.468 | 0.452 | 0 | 0.5 | 1 |
| *REL DUM t* | 7054 | 0.541 | 0.498 | 0 | 1 | 1 |

**Table 4** Correlation matrix of the dependent and the main explanatory variables. This table presents the Pearson correlations coefficients for the main variables used in our regressions. Table 1 provides the definitions and calculations for all variables.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) |
| *(1) Loan spread t* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| *(2) Audit rate t-1* | -0.364 | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (3) *Firm size t-1* | -0.357 | 0.214 | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (4) *ROA t-1* | -0.197 | 0.070 | 0.019 | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (5) *Liquidity t-1* | 0.058 | -0.075 | -0.190 | 0.024 | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |
| (6) *Tangibility t-1* | -0.049 | 0.016 | 0.136 | -0.132 | -0.223 | 1.000 |  |  |  |  |  |  |  |  |  |  |  |
| (7) *Leverage t-1* | 0.226 | 0.054 | -0.025 | -0.065 | -0.206 | 0.034 | 1.000 |  |  |  |  |  |  |  |  |  |  |
| (8) *Cash ETR t-1* | 0.208 | -0.054 | -0.018 | -0.220 | -0.050 | 0.145 | 0.124 | 1.000 |  |  |  |  |  |  |  |  |  |
| (9) *Altman's z-score t-1* | -0.134 | -0.009 | -0.020 | 0.359 | 0.121 | -0.176 | -0.322 | -0.218 | 1.000 |  |  |  |  |  |  |  |  |
| (10) *S&P 500 t-1* | -0.396 | 0.147 | 0.607 | 0.114 | -0.104 | 0.027 | -0.024 | -0.085 | 0.011 | 1.000 |  |  |  |  |  |  |  |
| (11) *INV Grade t-1* | -0.165 | 0.044 | 0.132 | 0.040 | -0.031 | 0.008 | -0.013 | -0.056 | 0.018 | 0.153 | 1.000 |  |  |  |  |  |  |
| (12) *Listed t-1* | -0.176 | 0.009 | 0.136 | 0.106 | 0.002 | -0.067 | -0.128 | -0.075 | 0.103 | 0.286 | 0.031 | 1.000 |  |  |  |  |  |
| (13) *Loan size t* | -0.323 | 0.186 | 0.693 | 0.064 | -0.116 | 0.081 | -0.013 | -0.061 | -0.012 | 0.449 | 0.093 | 0.165 | 1.000 |  |  |  |  |
| (14) *Loan maturity t* | 0.183 | -0.043 | -0.112 | 0.029 | 0.069 | -0.060 | 0.014 | 0.011 | 0.005 | -0.102 | -0.080 | 0.023 | 0.029 | 1.000 |  |  |  |
| (15) *RIA t* | -0.053 | -0.068 | 0.117 | 0.024 | 0.018 | -0.003 | -0.033 | -0.015 | 0.080 | 0.054 | 0.032 | 0.075 | 0.119 | -0.005 | 1.000 |  |  |
| (16) *RIN t* | -0.052 | -0.072 | 0.123 | 0.020 | 0.016 | 0.004 | -0.033 | -0.008 | 0.074 | 0.049 | 0.029 | 0.078 | 0.113 | -0.008 | 0.978 | 1.000 |  |
| (17) *REL DUM t* | -0.095 | -0.010 | 0.067 | 0.024 | 0.003 | 0.003 | -0.012 | -0.021 | 0.060 | 0.055 | 0.042 | 0.018 | 0.062 | -0.077 | 0.819 | 0.794 | 1.000 |

**Table 5** The effect of IRS monitoring on the cost of bank loans (hypothesis *H.1*) – baseline and 2SLS IV estimations. Models 1-3 present the results from regressing bank loan spreads on the Internal Revenue Service (IRS) audit rates after controlling for loan-level characteristics (model 2) and firm-level characteristics (model 3) based on OLS tests. Models 4-6 present the results from regressing bank loan spreads on the predicted IRS audit rates after controlling for firm and loan-level characteristics based on 2SLS IV regressions. We use two instruments: i) the two-year lagged natural logarithm of the number of corporate tax returns filed in the size class of the borrowing firm. ii) the one-year lagged average audit rate of the size classes other than the one of the borrowing firm. Models 4 and 5 show the estimations from a two-stage instrumental procedure where we use the two instruments mentioned above separately, while model 6 includes both instruments simultaneously. UIT is the under-identification LM test by Kleibergen and Paap, and WIT is the Wald F-statistic of the weak identification test that must be higher than its critical value to reject the null. OIT is the over-identification test of Hansen. Table 1 provides the definitions and calculations for all variables.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | OLS | OLS | OLS | 2SLS IV | 2SLS IV | 2SLS IV |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | Loan  Spread | Loan  Spread | Loan  Spread | Loan  Spread | Loan  Spread | Loan  Spread |
| *Audit rate t-1* | -.021\*\*\* | -.022\*\*\* | -.02\*\*\* |  |  |  |
|  | (-3.126) | (-3.362) | (-3.221) |  |  |  |
| *Pred Audit rate t-1* |  |  |  | -.038\*\*\* | -.045\*\*\* | -.04\*\*\* |
|  |  |  |  | (-3.819) | (-3.506) | (-4.27) |
| *Loan size t* |  | -.196\*\*\* | -.081\*\*\* | -.079\*\*\* | -.079\*\*\* | -.079\*\*\* |
|  |  | (-12.861) | (-7.442) | (-7.233) | (-7.226) | (-7.232) |
| *Loan maturity t* |  | .132\*\*\* | .088\*\*\* | .084\*\*\* | .085\*\*\* | .084\*\*\* |
|  |  | (6.122) | (4.691) | (4.471) | (4.468) | (4.47) |
| *Covenant t* |  | -.099\*\* | -.046 | -.063 | -.056 | -.061 |
|  |  | ( -2.01) | (-1.13) | (-0.74) | (-0.69) | (-0.72) |
| *Firm Size t-1* |  |  | -.128\*\*\* | -.129\*\*\* | -.13\*\*\* | -.129\*\*\* |
|  |  |  | (-6.261) | (-6.249) | (-6.232) | (-6.246) |
| *ROA t-1* |  |  | -2.971\*\*\* | -2.956\*\*\* | -2.949\*\*\* | -2.954\*\*\* |
|  |  |  | (-4.699) | (-4.659) | (-4.657) | (-4.659) |
| *Liquidity t-1* |  |  | .009\* | .01\* | .01\* | .01\* |
|  |  |  | (1.743) | (1.748) | (1.718) | (1.742) |
| *Tangibility t-1* |  |  | -.165\*\*\* | -.162\*\*\* | -.162\*\*\* | -.162\*\*\* |
|  |  |  | (-4.247) | (-4.14) | (-4.132) | (-4.138) |
| *Leverage t-1* |  |  | .52\*\*\* | .537\*\*\* | .537\*\*\* | .537\*\*\* |
|  |  |  | (7.296) | (7.432) | (7.446) | (7.436) |
| *Cash ETR t-1* |  |  | .401\*\*\* | .377\*\*\* | .376\*\*\* | .377\*\*\* |
|  |  |  | (6.558) | (6.196) | (6.187) | (6.194) |
| *Altman-zscore t-1* |  |  | -.06\*\*\* | -.058\*\*\* | -.058\*\*\* | -.058\*\*\* |
|  |  |  | (-4.483) | (-4.444) | (-4.483) | (-4.454) |
| *S&P500 t-1* |  |  | -.2\*\*\* | -.194\*\*\* | -.193\*\*\* | -.194\*\*\* |
|  |  |  | (-4.46) | (-4.29) | (-4.259) | (-4.282) |
| *INV Grade t-1* |  |  | -.226\*\*\* | -.227\*\*\* | -.227\*\*\* | -.227\*\*\* |
|  |  |  | (-4.411) | (-4.417) | (-4.421) | (-4.418) |
| *Listed t-1* |  |  | -.049 | -.044 | -.044 | -.044 |
|  |  |  | (-1.225) | (-1.102) | (-1.096) | (-1.1) |
| Constant | 5.564\*\*\* | 6.516\*\*\* | 7\*\*\* |  |  |  |
|  | (26.925) | (29.771) | (28.341) |  |  |  |
| First stage |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| *Ln tax returns of size class t-2* |  |  |  | -8.929\*\*\*  (-11.29) |  | -4.99\*\*\*  (-5.87) |
| *Average IRS audit rate of other size classes t-1* |  |  |  |  | -.821\*\*\*  (-11.49) | -.6955\*\*\*  (-10.38) |
| Observations | 6951 | 6951 | 6951 | 6848 | 6848 | 6848 |
| R-squared | .474 | .533 | .625 | .284 | .283 | .284 |
| LM test p-value (UIT) |  |  |  | .000 | .000 | .000 |
| Wald F-Test (WIT) |  |  |  | 131.957 | 127.514 | 79.307 |
| with critical value |  |  |  | 16.38 | 16.38 | 19.93 |
| Hansen J p-value (OIT) |  |  |  | - | - | 0.5297 |
| Control variables in 1st stage |  |  |  | Y | Y | Y |
| Loan purpose & type FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y | Y | Y |

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering.

**Table 6** The conditioning effect of lending relationships on the association between IRS monitoring and the cost of bank loans (hypotheses *H.2A* vs. *H.2B*). This table presents the results from regressing bank loan spreads on the interaction between IRS audit rates and relationship lending variables after controlling for firm and loan-level characteristics. We use three relationship lending variables: RIA, RIN, and REL DUM. Table 1 provides the definitions and calculations for all the other control variables.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | Loan  Spread | Loan  Spread | Loan  Spread | Loan  Spread | Loan  Spread | Loan  Spread |
| *Audit rate t-1* | -.02\*\*\* | -.018\*\*\* | -.02\*\*\* | -.018\*\*\* | -.02\*\*\* | -.018\*\*\* |
|  | (-3.216) | (-2.915) | (-3.217) | (-2.931) | (-3.194) | (-2.911) |
| *RIA t* | -.011 | .23\*\*\* |  |  |  |  |
|  | (-.486) | (3.043) |  |  |  |  |
| *Audit rate t-1 \* RIA t* |  | -.008\*\*\* |  |  |  |  |
|  |  | (-3.236) |  |  |  |  |
| *RIN t* |  |  | -.01 | .229\*\*\* |  |  |
|  |  |  | (-.434) | (2.993) |  |  |
| *Audit rate t-1\*RIN t* |  |  |  | -.008\*\*\* |  |  |
|  |  |  |  | (-3.168) |  |  |
| *REL DUM t* |  |  |  |  | -.015 | .208\*\*\* |
|  |  |  |  |  | (-.684) | (2.893) |
| *Audit rate t-1\*REL DUM t* |  |  |  |  |  | -.007\*\*\* |
|  |  |  |  |  |  | (-3.179) |
| Constant | 7.005\*\*\* | 6.94\*\*\* | 7.004\*\*\* | 6.943\*\*\* | 7.002\*\*\* | 6.936\*\*\* |
|  | (28.435) | (28.279) | (28.458) | (28.315) | (28.377) | (28.223) |
| Observations | 6951 | 6951 | 6951 | 6951 | 6951 | 6951 |
| R-squared | .625 | .626 | .625 | .626 | .625 | .626 |
| Control Variables | Y | Y | Y | Y | Y | Y |
| Loan purpose & type FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y | Y | Y |

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering.

**Table 7** The conditioning effect of lending relationships on the association between IRS monitoring and the cost of bank loans (hypotheses *H.2A* vs. *H.2B*) – The role of credible access to the public markets of external financing. This table presents the results from regressing bank loan spreads on the interaction among IRS audit rates, relationship lending variables, and proxies for credible access to the public markets after controlling for firm and loan-level characteristics. We use three variables that capture firms’ access to the public markets. In Panel A, we use a dummy variable that equals one for firms that are listed on a stock exchange and zero otherwise. In Panel B, we use a dummy variable that equals one for firms that are among the SP&500 firms and zero otherwise. Lastly, in Panel C, we use a dummy variable that equals one if a borrowing firm has an equal to or above "BBB-" long-term credit rating by S&P while it equals zero if the rating is below "BBB-" or if the firm is unrated.

|  |  |  |  |
| --- | --- | --- | --- |
| **Panel A**: Listed firms | | | |
|  | (1) | (2) | (3) |
|  | Loan  spread | Loan  spread | Loan  spread |
| *Audit rate t-1* | -.019\*\*\* | -.019\*\*\* | -.019\*\*\* |
|  | (-2.99) | (-3.008) | (-2.994) |
| *Listed- t-1* | -.014 | -.013 | -.005 |
|  | (-.345) | (-.311) | (-.128) |
| *RIA t* | .227\*\*\* |  |  |
|  | (3.008) |  |  |
| *Audit rate t-1\* RIA t* | -.005\*\* |  |  |
|  | (-2.029) |  |  |
| *Audit rate t-1\* RIA t \*Listed- t-1* | -.003\* |  |  |
|  | (-1.74) |  |  |
| *RIN t* |  | .226\*\*\* |  |
|  |  | (2.955) |  |
| *Audit rate t-1\*RIN t* |  | -.005\* |  |
|  |  | (-1.961) |  |
| *Audit rate t-1\*RIN t \* Listed- t-1* |  | -.003\* |  |
|  |  | (-1.791) |  |
| *REL DUM t* |  |  | .208\*\*\* |
|  |  |  | (2.901) |
| *Audit rate t-1\*REL DUM t* |  |  | -.005\* |
|  |  |  | (-1.77) |
| *Audit rate t-1\*REL DUM t \* Listed t-1* |  |  | -.004\*\* |
|  |  |  | (-2.19) |
| Constant | 6.932\*\*\* | 6.935\*\*\* | 6.926\*\*\* |
|  | (28.267) | (28.29) | (28.19) |
| Observations | 6951 | 6951 | 6951 |
| R-squared | .627 | .627 | .627 |
| **Panel B:** S&P500 firms | | | |
| *Audit rate t-1* | -.019\*\*\* | -.019\*\*\* | -.019\*\*\* |
|  | (-2.99) | (-3.01) | (-3.043) |
| *S&P500-1* | -.143\*\*\* | -.135\*\*\* | -.115\*\* |
|  | (-2.945) | (-2.742) | (-2.568) |
| *RIA t* | .209\*\*\* |  |  |
|  | (2.77) |  |  |
| *Audit rate t-1\* RIA t* | -.006\*\* |  |  |
|  | (-2.366) |  |  |
| *Audit rate t-1\* RIA t \*S&P500 t-1* | -.003\*\* |  |  |
|  | (-2.347) |  |  |
| *RIN t* |  | .205\*\*\* |  |
|  |  | (2.699) |  |
| *Audit rate t-1\*RIN t* |  | -.006\*\* |  |
|  |  | (-2.221) |  |
| *Audit rate t-1\*RIN t \*S&P500 t-1* |  | -.004\*\*\* |  |
|  |  | (-2.637) |  |
| *REL DUM t* |  |  | .178\*\* |
|  |  |  | (2.475) |
| *Audit rate t-1\*REL DUM t* |  |  | -.004\* |
|  |  |  | (-1.709) |
| *Audit rate t-1\*REL DUM t \*S&P500 t-1* |  |  | -.006\*\*\* |
|  |  |  | (-4.069) |
| Constant | 6.946\*\*\* | 6.947\*\*\* | 6.944\*\*\* |
|  | (28.322) | (28.354) | (28.399) |
| Observations | 6951 | 6951 | 6951 |
| R-squared | .627 | .627 | .629 |
| **Panel C:** Investment grade firms | | | |
| *Audit rate t-1* | -.018\*\*\* | -.018\*\*\* | -.018\*\*\* |
|  | (-2.92) | (-2.937) | (-2.926) |
| *INV Grade t-1* | -.184\*\* | -.183\*\* | -.117\* |
|  | (-2.36) | (-2.354) | (-1.717) |
| *RIA t* | .226\*\*\* |  |  |
|  | (2.979) |  |  |
| *Audit rate t-1\* RIA t* | -.008\*\*\* |  |  |
|  | (-3.09) |  |  |
| *Audit rate t-1\* RIA t \*INV GRADE t-1* | -.002 |  |  |
|  | (-.834) |  |  |
| *RIN t* |  | .225\*\*\* |  |
|  |  | (2.932) |  |
| *Audit rate t-1\*RIN t* |  | -.008\*\*\* |  |
|  |  | (-3.022) |  |
| *Audit rate t-1\*RIN t \* INV GRADE t-1* |  | -.002 |  |
|  |  | (-.871) |  |
| *REL DUM t* |  |  | .2\*\*\* |
|  |  |  | (2.78) |
| *Audit rate t-1\*REL DUM t* |  |  | -.007\*\*\* |
|  |  |  | (-2.852) |
| *Audit rate t-1\*REL DUM t \* INV GRADE t-1* |  |  | -.006\*\*\* |
|  |  |  | (-2.652) |
| Constant | 6.942\*\*\* | 6.945\*\*\* | 6.939\*\*\* |
|  | (28.295) | (28.333) | (28.279) |
| Observations | 6951 | 6951 | 6951 |
| R-squared | .626 | .626 | .627 |
| **Control variables and FE included in All Panels** | | | |
| Control variables  Double interaction terms | Y  Y | Y  Y | Y  Y |
| Loan purpose & type FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| Lead Lender FE | Y | Y | Y |
| Industry FE | Y | Y | Y |
| Size class FE | Y | Y | Y |

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering.

**Table 8** The conditioning effect of lending relationships on the association between IRS monitoring and the cost of bank loans (H2A vs H2B) - Split sample analysis. This table presents the results from regressing bank loan spreads on the interaction between IRS audit rates and relationship lending variables after controlling for firm and loan-level characteristics across two subsamples: the low lending relationship subsample and the high lending relationship subsample. We split our loan level dataset based on the median value of the two continuous lending relationship variables: RIA and RIN. Table 1 provides the definitions and calculations for all the other control variables.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Panel A: Low Lending Rel. | | | | Panel B: High Lending Rel. | | |
|  | (1) | (2) | (3) | | (4) |
| VARIABLES | Model | Model | Model | | Model |
|  |  |  |  | |  |
| *Audit rate t-1* | -0.019\*\* | -0.018\*\* | -0.012 | | -0.014 |
|  | (-2.572) | (-2.487) | (-0.935) | | (-1.066) |
| *RIA t* | 0.153\*\*\* |  | 0.388 | |  |
|  | (3.096) |  | (1.408) | |  |
| *Audit rate t-1\* RIA t* | -0.004\*\* |  | -0.019\*\* | |  |
|  | (-2.433) |  | (-2.13) | |  |
| *RIN t* |  | 0.236\*\*\* |  | | 0.344 |
|  |  | (4.092) |  | | (1.158) |
| *Audit rate t-1\*RIN t* |  | -0.006\*\*\* |  | | -0.017\*\* |
|  |  | (-3.23) |  | | (2.231) |
| Constant | 6.877\*\*\* | 6.863\*\*\* | 7.022\*\*\* | | 7.058\*\*\* |
|  | (23.596) | (23.592) | (15.862) | | (15.717) |
|  |  |  |  | |  |
| Observations | 3,434 | 3,408 | 3,496 | | 3,519 |
| R-squared | 0.649 | 0.650 | 0.644 | | 0.644 |
| Control Variables | Y | Y | Y | | Y |
| Loan purpose & type FE | Y | Y | Y | | Y |
| Lead lender FE | Y | Y | Y | | Y |
| Year FE | Y | Y | Y | | Y |
| Industry FE | Y | Y | Y | | Y |
| Size class FE | Y | Y | Y | | Y |

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering.

**Table 9** The conditioning effect of lending relationships on the association between IRS monitoring and the cost of bank loans (H2A vs H2B)- Split sample analysis. – The role of credible access to the public markets for external financing. This table presents the results from regressing bank loan spreads on the interaction among IRS audit rates, relationship lending variables, and proxies for credible access to the public markets after controlling for firm and loan-level characteristics across two subsamples: the low lending relationship subsample and the high lending relationship subsample. We split our loan level dataset based on the median value of the two continuous lending relationship variables: RIA and RIN. We use three variables that capture firms’ access to the public markets. In Panel A, we use a dummy variable that equals one for firms that are listed in a stock exchange market and zero otherwise. In Panel B, we use a dummy variable that equals one for firms that are among the SP&500 firms and zero otherwise. In Panel C, we use a dummy variable that equals one if a borrowing firm has an equal to or above "BBB-" long-term credit rating by S&P while it takes the value of zero if the rating is below "BBB-" or if the firm is unrated.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Panel A: Listed Firms | Low Lending Relationship | | High Lending Relationship | |
|  | (1) | (2) | (3) | (4) |
| VARIABLES | Model | Model | Model | Model |
|  |  |  |  |  |
| *Audit rate t-1* | -0.018\*\* | -0.018\*\* | -0.012 | -0.014 |
|  | (-2.553) | (-2.478) | (-1.006) | (-1.121) |
| *Listed- t-1* | -0.056 | -0.064 | 0.181 | 0.228 |
|  | (-1.379) | (-1.631) | (1.288) | (1.586) |
| *RIA t* | 0.149\*\*\* |  | 0.385 |  |
|  | (3.07) |  | (1.394) |  |
| *Audit rate t-1\* RIA t* | -0.005\*\*\* |  | -0.012 |  |
|  | (-2.871) |  | (-1.239) |  |
| *Audit rate t-1\* RIA t \*Listed- t-1* | 0.001 |  | -0.009\*\* |  |
|  | (1.536) |  | (-2.233) |  |
| *RIN t* |  | 0.225\*\*\* |  | 0.342 |
|  |  | (3.976) |  | (1.15) |
| *Audit rate t-1\* RIN t* |  | -0.007\*\*\* |  | -0.009 |
|  |  | (-3.655) |  | (-0.866) |
| *Audit rate t-1\* RIN t \*Listed- t-1* |  | 0.001 |  | -0.011\*\* |
|  |  | (1.239) |  | (-2.163) |
| Constant | 6.888\*\*\* | 6.878\*\*\* | 6.869\*\*\* | 6.876\*\*\* |
|  | (23.627) | (23.675) | (15.046) | (14.844) |
| Observations | 3,434 | 3,408 | 3,496 | 3,519 |
| R-squared | 0.649 | 0.651 | 0.645 | 0.645 |
| Panel B: S&P500 Firms | Low Lending Relationship | | High Lending Relationship | |
|  | (1) | (2) | (3) | (4) |
| VARIABLES | Model | Model | Model | Model |
| *Audit rate t-1* | -0.019\*\* | -0.018\*\* | -0.013 | -0.018 |
|  | (-2.571) | (-2.486) | (-1.062) | (-1.396) |
| *S&P500 t-1* | -0.219\*\*\* | -0.220\*\*\* | 0.173\* | 0.194\* |
|  | (-4.025) | (-4.035) | (1.662) | (1.684) |
| *RIA t* | 0.152\*\*\* |  | 0.380 |  |
|  | (2.973) |  | (1.337) |  |
| *Audit rate t-1\* RIA t* | -0.004\*\* |  | -0.013 |  |
|  | (-2.449) |  | (-1.386) |  |
| *Audit rate t-1\* RIA t \*S&P500 t-1* | 0.000 |  | -0.014\*\*\* |  |
|  | (0.954) |  | (-3.93) |  |
| *RIN t* |  | 0.234\*\*\* |  | 0.268 |
|  |  | (4.066) |  | (0.90) |
| *Audit rate t-1\*RIN t* |  | -0.006\*\*\* |  | -0.007 |
|  |  | (-3.233) |  | (-0.718) |
| *Audit rate t-1\*RIN t \*S&P500 t-1* |  | 0.000 |  | -0.018\*\*\* |
|  |  | (0.292) |  | (-4.895) |
| Constant | 6.877\*\*\* | 6.865\*\*\* | 6.915\*\*\* | 6.976\*\*\* |
|  | (23.566) | (23.562) | (15.539) | (15.663) |
| Observations | 3,434 | 3,408 | 3,496 | 3,519 |
| R-squared | 0.649 | 0.650 | 0.648 | 0.650 |
| Panel C: Investment Grade Firms | Low Lending Relationship | | High Lending Relationship | |
|  | (1) | (2) | (3) | (4) |
| VARIABLES | Model | Model | Model | Model |
| *Audit rate t-1* | -0.019\*\* | -0.018\*\* | -0.012 | -0.014 |
|  | (-2.57) | (-2.481) | (-0.942) | (-1.085) |
| *INV Grade t-1* | -0.235\*\*\* | -0.226\*\*\* | 0.006 | -0.040 |
|  | (-2.958) | (-2.919) | (0.03) | (-0.184) |
| *RIA t* | 0.153\*\*\* |  | 0.377 |  |
|  | (3.086) |  | (1.371) |  |
| *Audit rate t-1\* RIA t* | -0.004\*\* |  | -0.019\*\* |  |
|  | (-2.468) |  | (-2.053) |  |
| *Audit rate t-1\* RIA t \*INV GRADE t-1* | 0.000 |  | -0.007 |  |
|  | (0.042) |  | (-0.99) |  |
| *RIN t* |  | 0.236\*\*\* |  | 0.334 |
|  |  | (4.115) |  | (1.129) |
| *Audit rate t-1\*RIN t* |  | -0.006\*\*\* |  | -0.017\* |
|  |  | (-3.217) |  | (-1.686) |
| *Audit rate t-1\*RIN t \* INV GRADE t-1* |  | -0.000 |  | -0.006 |
|  |  | (-0.211) |  | (-0.766) |
| Constant | 6.877\*\*\* | 6.863\*\*\* | 7.020\*\*\* | 7.060\*\*\* |
|  | (23.600) | (23.582) | (15.887) | (15.742) |
| Observations | 3,434 | 3,408 | 3,496 | 3,519 |
| R-squared | 0.649 | 0.650 | 0.645 | 0.644 |
| **Control Variables and FE included in All Panels** |  |  |  |  |
| Control Variables | Y | Y | Y | Y |
| Double interaction terms | Y | Y | Y | Y |
| Loan purpose & type FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y |
| Industry | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y |

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering.

**List of Figures**

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**Fig 1. The effect of IRS audit rate on loan spreads by different lending relationship intensity (RIA).**

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**Fig 2. The effect of IRS audit rate on loan spreads by different lending relationship intensity (RIN).**

**Internet Appendix for "Does IRS monitoring matter for the cost of bank loans?"**

In this Internet Appendix, we present and discuss the results of additional robustness tests and further analysis that we briefly discuss but do not tabulate in our paper "*Does IRS monitoring matter for the cost of bank loans?*"

In Table IA.1, we define the additional variables we use in the tests of the internet appendix.

*Table IA.1*

**IA.1 Further analysis: Non-price loan contract terms**

In further analysis, we investigate the association between IRS monitoring and some non-price terms in loan contracts. The results from these tests are available in Table IA.2.

*Table IA.2*

In model 1 of Table IA.2, we use a probit regression and find that *Audit rate t-1* is associated negatively and significantly at the 5% level with the probability that a loan will contain covenants. This result provides further evidence in favor of ***H.1***. In model 2, we show that the interaction between *Audit rate t-1* and *RIA* is negative and significant at the 5% level. This finding is consistent with ***H.2B***. We also test for the effects of IRS monitoring on loan size (models 3 and 4 of Table IA.2) and loan maturity (models 5 and 6 of Table IA.2), but we do not find significant results. Overall, we provide some evidence that IRS monitoring results in less strict non-price terms in loan contracts.

**IA.2 Other tests for hypothesis H.1: alternative measures of borrowing firm size, size non-linearities, time trends, and geographic variation in IRS monitoring**

In this section, we examine whether our findings hold when we control for alternative measures of firm size. Hence, in models 1 and 2 of Panel A in Table IA.3, we replace the natural logarithm of total assets as a measure of firm size with the natural logarithm of total equity and sales, respectively. We find that both these size proxies display a negative and significant association with the cost of bank loans at the 1% level. More importantly, the estimations in models 1 and 2 of Panel A in Table IA.3 support the findings in the main manuscript that borrowers benefit from lower loan spreads when IRS monitoring is more stringent. The coefficients for *Audit rate t-1* are negative and significant at the 5% and 1% levels in models 1 and 2 of Panel A in Table IA.3, respectively. These findings are similar to the baseline results in statistical and economic significance. In model 3 of Panel A in Table IA.2, we add the squared and cubed values of firm size to account for potential non-linearities stemming from this variable. The effect of *Audit rate t-1* remains negative and significant at the 1% level.

*Table* *IA.3*

The other source of variation in *Audit rate t-1* is the within-size class variation. The main analysis includes year fixed effects to account for macro-level shocks that affect all firms. However, it could be possible that there are time trends during the sample period that could differentially affect the firms belonging to specific size classes. These trends could affect our findings if they simultaneously affect the cost of bank loans. For example, suppose larger firms become riskier over time than smaller firms in a way that is not entirely captured by the time-varying control variables. In that case, this omission could drive our findings. We add time trends for each size class to address these concerns in model 4 of Panel A in Table IA.3. After controlling for these trends, we still find that *Audit rate t-1* has a negative and significant effect on the cost of bank loans at the 1% level that supports ***H.1***.

To further attenuate any concerns for *Audit rate t-1*, we introduce a source of geographic variation in IRS monitoring. Kubick et al. (2017) show that the probability of an IRS audit is higher when a firm is closer to an IRS office (territory manager office). Therefore, using data from Kubick et al. (2017), we create a variable that captures the number of IRS offices in the state of each borrowing firm. Then we run models that interact this variable (*IRS Offices State*) with *Audit rate t-1*.

In the first model of Panel B in Table IA.3, we find that IRS *Audit rate t-1* displays a negative and significant association with the cost of bank loans after controlling for *IRS Offices State*. We also control for the natural log of the state income per capita (*State Income Cap*), the state unemployment rate (*State Unemployment*), and the level of education in each state (*State Education*). We source these state-level control variables from the Bureau of Economic Analysis (BEA). In model 2 of Panel B in Table IA.3, we find that the interaction between *Audit rate t-1* and *IRS Offices State* is negative and significant at the 5% level. In the same model, the individual effect of *Audit rate t-1* is negative and significant at the 5% level. One concern is that the proximity of IRS offices in a state could relate to the state's size. In model 3 of Panel B in Table IA.3, we control for the size of each state using the natural log of the population (*State Population*), and the results are similar.

These findings denote that the negative association between the IRS audit rate and the cost of bank loans is pronounced for firms in states with more IRS offices. Hence, introducing this proxy of geographic variation in IRS monitoring provides further evidence that supports ***H.1***.

**IA.3 Alternative IRS monitoring measures**

Our analysis in the main manuscript focuses on the effect of *Audit rate t-1* on the cost of bank loans. Following the study of Guedhami and Pittman (2008), we supplement our analysis with several alternative proxies for IRS tax enforcement that capture further aspects of IRS monitoring. These are available for the 1992-2003 period and do not hinge on borrowers' size like the IRS audit rates. Therefore, these measures could corroborate our baseline findings in the main manuscript.

The first set of these alternative measures reflects the yearly levels of IRS staffing (normalized by the yearly corporate tax returns). The estimations are available in models 1-3 in Table IA.3.[[11]](#footnote-11) They show that the coefficients for the revenue agents (model 1), employees (model 2), and criminal investigators (model 3) of the IRS enter the regressions negatively and significantly at the 1% level. These findings indicate that the IRS staffing levels decrease loan spreads. Therefore, these results are consistent with ***H.1***.

*Table* IA.4

The second set of alternative IRS monitoring variables comprises the normalized number of criminal referrals, criminal prosecutions, and civil penalties for tax fraud and negligence against corporations that the IRS levies. The results are available in models 4-7 of Table IA.4. These models show a negative and significant association at the 1% level. Overall, the findings in Table IA.4 support ***H.1*** about the negative association between IRS monitoring and the cost of bank loans.

*Table IA.5*

To provide further empirical evidence in support of ***H.2B***,weperform estimations that comprise the interactions between the alternative measures of IRS monitoring (revenue agents, employees, criminal investigators, fraud penalties, negligence penalties, criminal referrals, and criminal prosecutions) with our main lending relationship variable (*RIA*). Table IA.5 shows the findings from this exercise. In most models, the interactions emerge as negative, significant, and consistent with ***H.2B***.

**IA.4 Controlling for additional tax avoidance measures**

In this section, we examine if IRS monitoring continues to negatively associate with the cost of syndicated loans after controlling for several additional tax avoidance measures. This exercise is important in the context of this study because we are interested in the presence of a negative effect of IRS monitoring on loan pricing that is incremental to the effect of tax avoidance and consistent with its monitoring and informational role in financial markets.

In the baseline model in subsection 4.1 of the analysis in the main manuscript, we use the cash effective tax rate (*CASH ETR*) to control for tax avoidance. However, single-year effective tax rates tend to have large year-to-year fluctuations and may not fully reflect a firm's long-run tax avoidance strategy (Dyreng et al. 2008; Shevlin et al. 2013). For this reason, we use two additional measures of the cash effective tax rate.[[12]](#footnote-12) The first such measure is the lagged to the loan issuance five-year rolling average of the cash effective tax rate (*ROLL CASH ETR*). The second is the sum of total expenses over the last five years before the loan issuance divided by the sum of the pre-tax book income less special items over the same five-year period (*SUM CASH ETR*). As in the case of the cash effective tax rate in the baseline model, we multiply these variables by minus one (-1) to denote higher tax avoidance. In models 1 and 2 of Table IA.6, we find that the association between *IRS Audit rate t-1* and the cost of bank loans continues to be negative and significant at the 1% level.

*Table IA.6*

Next, we use the GAAP effective tax rate that is the ratio of total tax expenses divided by pre-tax book income less special items as an alternative tax avoidance measure. This measure captures aggressive strategies of tax planning that target permanent tax savings (Chen et al. 2010; Cen et al. 2017).[[13]](#footnote-13) Similar to the cash effective tax rate case, we use three variants of the GAAP effective tax rate. The first is the simple one-year lagged to the loan issuance GAAP effective tax rate (*GAAP ETR*). We also use the lagged to the loan issuance five-year rolling average of the GAAP effective tax rate (*ROLL GAAP ETR*) and the ratio of the sum of total expenses over the last five years before the loan issuance divided by the sum of the pre-tax book income less special items over the same five-year period (*SUM GAAP ETR*). Again, we multiply these variables by minus one (-1) to represent higher tax avoidance. In models 3, 4, and 5 of Table IA.6, we continue to find that *IRS audit rate t-1* has a negative and significant relationship with the cost of bank loans at the 1% level.

Furthermore, we use two additional measures of tax avoidance. The first of these is the Manzon and Plesko (2002) one-year lagged to the issuance of a loan book-tax difference (*BT*). This tax avoidance measure is a direct estimation of book-tax differences and has been used in several other studies (e.g., Hasan et al. 2014; Francis et al. 2014). The second is the one-year lagged to the issuance of a loan tax sheltering score of a firm. Wilson (2009) uses cases of actual tax sheltering and provides models for empirical applications that estimate the likelihood (through a tax sheltering score) that a firm engages in activities related to tax shelters. We follow Rego and Wilson (2012) and Francis et al. (2014) and use the model in Column 3 of Table 5 of Wilson (2009) to estimate the tax sheltering scores (*SHELTER*). A higher tax sheltering score indicates a higher probability of engaging in tax sheltering. Note that the number of observations for the book-tax difference (*BT*) and the tax sheltering score (*SHELTER*) measures of tax avoidance is lower than in the case of the effective tax rate and cash effective tax measures because of missing observations for some of the component variables needed to construct them. In models 6 and 7 of Table IA.6, the effect of IRS *Audit rate t-1* on the cost of bank loans remains negative and significant at the 10% level even after controlling for the book-tax difference and the tax sheltering score tax avoidance measures.

Finally, in all models of Table IA.6, we find that all the tax avoidance measures have a positive and significant association with the cost of bank loans, which is consistent with the literature (see, e.g., Hasan et al. 2014). Overall, the findings from this exercise provide additional empirical evidence that the negative association between IRS monitoring and the cost of bank loans is incremental to the effect of tax avoidance. These findings provide further support to hypothesis ***H.1*** about the negative association between IRS monitoring and the cost of bank loans.

**IA.6 Alternative clustering of standard errors**

In the main analysis of the paper, we follow the standard in the literature of the determinants of the cost of bank loans, and we have clustered standard errors at the borrowing firm level because each one usually obtains multiple loan facilities. However, the main explanatory variable of interest (*Audit rate t-1*) is at the size class level. Furthermore, most of the observations in the sample comprise loan facilities to borrowing firms belonging to the largest IRS-defined size class (asset size > $250m). To deal with this issue, we use models where the clustering of the standard errors is at the size class and year levels because the IRS *Audit rate t-1* changes both by size class and year. These estimations are available in models 1 and 2 of Table IA.7. Model 1 is the baseline specification, while model 2 is the specification that includes the interaction between *Audit rate t-1* and the relationship intensity variable (*RIA*). In both models, we find that the coefficient for IRS *Audit rate t-1* is negative and significant at the 5% level. In model 2, we find that the interaction *Audit rate t-1\*RIA* is also negative and significant at the 1% level. Furthermore, we estimate models in which we cluster the standard errors by borrowing firm and bank pairs because lending relationships are based on such pairs. The findings from these specifications are in models 3 and 4 of Table IA.7. The results continue to support the ***H.1***and ***H.2B*** hypotheses.

*Table IA.7*

**IA.7 Other tests**

We examine if the negative relationship between IRS monitoring and the cost of bank loans remains significant if we exclude observations of loans to firms belonging to the largest IRS-defined size class (asset size > $250m). Most of the observations of the sample belong to this size group. In section IA.7, we remedied this by clustering the standard errors at the size class and year levels. Here, we further find that the association between IRS *Audit rate t-1* and the cost of bank loans remains negative and significant at the 5% level even when we exclude the largest IRS size class (see model 1 of Table IA.8). Additionally, in model 2 of Table IA.8, we reestimate the baseline model by controlling for the size of the syndicate. The results show that the coefficient for IRS *Audit rate t-1* remains negative and significant at the 1% level.

In the main analysis, we use lagged IRS audit rates since such rates become known with a lag and ease endogeneity concerns. However, banks may develop rational expectations about the level of contemporaneous IRS monitoring (i.e., the probability of an IRS audit). These include information on proposed IRS budgets on public record, news about structural and leadership changes in the IRS, IRS statements that indicate more stringent tax enforcement, and trends in government revenue. Hence, in model 3 of Table IA.8, we add the contemporaneous IRS *Audit rate t*,and we observe that its effect on the cost of bank loans is negative and significant at the 5% level. Finally, in model 4 of Table IA.8, we account for the state-level time-variant business tax climate index (*SBTX*) as firms in areas with better tax conditions, i.e., lower tax rates, are less likely to be audited by the tax agency as they have fewer incentives to avoid taxes. The results continue to show that the coefficient of the *Audit rate t-1* variableis negative and significant at the 1% level.

*Table IA.8*

**References of the Internet Appendix**

Cen, L., Maydew, E. L., Zhang, L., and Zuo, L. 2017. Customer–supplier relationships and corporate tax avoidance. *Journal of Financial Economics*, *123*(2), 377-394.

Chen, S., Chen, X., Cheng, Q., and Shevlin, T. 2010. Are family firms more tax aggressive than non-family firms? *Journal of Financial Economics*, *95*(1), 41-61.

Dyreng, S. D., Hanlon, M., and Maydew, E. L. 2008. Long-run corporate tax avoidance. T*he Accounting Review*, *83*(1), 61-82.

Francis, B. B., Hasan, I., Wu, Q., and Yan, M. 2014. Are female CFOs less tax aggressive? Evidence from tax aggressiveness. *The Journal of the American Taxation Association*, *36*(2), 171-202.

Guedhami, O., and Pittman, J. 2008. The importance of IRS monitoring to debt pricing in private firms. *Journal of Financial Economics*, *90*, 38-58.

Hanlon, M., and Heitzman, S. 2010. A review of tax research. *Journal of Accounting and Economics*, *50*(2-3), 127-178.

Hasan, I., Hoi, S., 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*, 109-130.

Kubick, T.R., Lockhart, G.B., Mills, L.F. and Robinson, J.R. 2017. IRS and corporate taxpayer effects of geographic proximity. *Journal of Accounting and Economics*, *63*(2), 428-453.

Manzon Jr, G. B., and Plesko, G. A. 2002. The relation between financial and tax reporting measures of income. *Tax L. Rev.*, *55*, 175.

Rego, S. O., and Wilson, R. 2012. Equity risk incentives and corporate tax aggressiveness. *Journal of Accounting Research*, *50*(3), 775-810.

Shevlin, T. J., Urcan, O., and Vasvari, F. P. 2013. Corporate tax avoidance and public debt costs. Working paper, Available at SSRN: <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2228601>

Wilson, J. 2009. An examination of corporate tax shelter participants. *The Accounting Review*, *84*, 969-999.

**List of Tables (Internet Appendix)**

**Table IA.1.**Information on variables used in the analyses of the Internet Appendix that are not defined in detail in the main manuscript

|  |  |  |
| --- | --- | --- |
| **Variables of the Internet Appendix Analyses** | | |
| Alternative IRS monitoring proxies | | |
| *IRS employees t-1* | Number of IRS employees divided by corporate tax returns in year t | TRAC |
| *IRS revenue agents t-1* | Number of IRS revenue agents divided by corporate tax returns in year t | TRAC |
| *IRS criminal investigators t-1* | Number of IRS criminal investigators divided by corporate tax returns in year t | TRAC |
| *IRS fraud penalties t-1* | Number of IRS fraud penalties divided by corporate tax returns in year t | TRAC |
| *IRS negligence penalties t-1* | Number of IRS negligence penalties divided by corporate tax returns in year t | TRAC |
| *IRS criminal referrals t-1* | Number of IRS criminal tax referrals divided by corporate tax returns in year t | TRAC |
| *IRS criminal prosecutions t-1* | Number of IRS criminal tax prosecutions divided by IRS criminal referrals in year t | TRAC |
| *IRS offices State* | The number of IRS offices (territory managers) in the state of each borrowing firm | Kubick et al. (2017) |
| Alternative size proxies |  |  |
| *Equity t-1* | The natural logarithm of total equity in year t-1 | COMPUSTAT |
| *Sales t-1* | The natural logarithm of total sales in year t-1 | COMPUSTAT |
| Other tax avoidance measures |  |  |
| *GAAP ETR t-1* | The ratio of tax expense (Compustat: TXT) to pre-tax income adjusted for special items [Compustat: (TXPD)/(PI − SPI)]. The measure is winsorized at the [0,1] interval. It also excludes observations with a negative or zero (PI − SPI), i.e., the effective tax rate is set as missing when the denominator is zero or negative. This measure is multiplied by (−1) so that an increase in the measure reflects increased tax avoidance. | COMPUSTAT |
| *SUM Cash ETR t-1* | Same method of measurement as Cash ETR t-1 but uses the sum of each item over the last five years. This measure is multiplied by (−1) so that an increase in the measure reflects increased tax avoidance. | COMPUSTAT |
| *SUM GAAP ETR t-1* | Same method of measurement as GAAP ETR t-1 but uses the sum of each item over the last five years. This measure is multiplied by (−1) so that an increase in the measure reflects increased tax avoidance. | COMPUSTAT |
| *ROLL Cash ETR5 t-1* | Five-year rolling average of the Cash ETR t-1 measure. This measure is multiplied by (−1) so that an increase in the measure reflects increased tax avoidance. | COMPUSTAT |
| *ROLL CAAP ETR5 t-1* | Five-year rolling average of the GAAP ETR t-1 measure. This measure is multiplied by (−1) so that an increase in the measure reflects increased tax avoidance. | COMPUSTAT |
| *BT t-1* | The Manzon and Plesko (2002) book-tax difference. BT is defined as (US domestic financial income - US domestic taxable income - Income taxes (State) - Income taxes (Other) - Equity in Earnings) / total assets. In Compustat terms BT = (PIDOM - TXFED/Statutory tax rate - TXS - TXO - ESUB)/ AT. Following the literature (e.g., Desai and Dharmapala 2007, Francis et al. 2014) we use only the observations with positive TXFED. | COMPUSTAT |
| *Shelter t-1* | This is the tax shelter score from the Wilson (2009) model as used in Rego and Wilson (2012). SHELTER = -4.30 + 6.63 \* BT - 1.72 \* Leverage + 0.66 \* Firm Size + 2.26 \* ROA + 1.62 \* Foreign Income + 1.56 \* R&D. Following Francis et al. (2014), Foreign Income is an indicator that is set to equal one for firm observations that show foreign income and zero otherwise. R&D is the ratio of R&D expenses to total assets. All remaining variables are explained elsewhere in Table 1. | COMPUSTAT |

**Table IA.2.** Further Analysis **-** The effect of IRS monitoring on the non-price loan contract terms. This Table presents the results from regressing non-price loan contract terms on IRS audit rates after controlling for firm-level characteristics, loan-level characteristics (all models). Regressions are based on probit (models 1 and 2) and OLS tests (models 3-6).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | Covenant presence | Covenant presence | Loan  size | Loan  size | Loan  maturity | Loan  maturity |
| *Audit rate t-1* | -.202\*\* | -.179 | .001 | .002 | .003 | .002 |
|  | (-2.12) | (-1.638) | (.119) | (.201) | (.429) | (.309) |
| *RIA t* | .254 | 1.708\*\* | .073\*\* | .167 | -.051\*\*\* | -.141\*\* |
|  | (1.601) | (2.393) | (2.075) | (1.317) | (-2.806) | (-2.345) |
| *Audit rate t-1\* RIA t* |  | -.057\*\* |  | -.003 |  | .003 |
|  |  | (-2.107) |  | (-.81) |  | (1.511) |
| Constant | 8.267\*\*\* | 7.647\*\*\* | 1.888\*\*\* | 1.87\*\*\* | .945\*\*\* | .962\*\*\* |
|  | (3.124) | (2.835) | (5.147) | (5.117) | (3.96) | (4.026) |
| Observations | 6951 | 6951 | 6951 | 6951 | 6951 | 6951 |
| R-squared | - | - | .602 | .602 | .39 | .39 |
| Pseudo R-squared | 0.466 | 0.469 | - | - | - | - |
| Control Variables | Y | Y | Y | Y | Y | Y |
| Loan purpose & type FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y | Y | Y |
| Indusrtry FE | Y | Y | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y | Y | Y |

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering.

**Table IA.3.** Alternative size measures, size non-linearities, and size-class time trends for borrowing firm (Panel A) and interaction of IRS audit rates with a geographic source of variation in IRS monitoring (Panel B). Models 1-4 of Panel A present the results from regressing bank loan spreads on IRS audit rates after controlling for firm-level and loan-level characteristics and using alternative size measures, size non-linearities, and size-class time trends. Models 1 and 2 comprise the natural logarithm of total equity and the natural logarithm of total sales as alternative proxies for size, respectively. Model 3 comprises the squared values and cubed values of the natural logarithm of total assets to control for non-linear effects. Model 4 comprises size-class trend effects to capture the time-varying characteristics that could affect firms that belong to each size class. Models 1-3 of Panel B present the results from regressing bank loan spreads on IRS audit rates after controlling for the presence of IRS offices in the state of the borrowing firms (*IRS Offices State*). We also control for the natural log of the state income per capita (*State Income Cap*), the state unemployment rate (*State Unemployment*), the level of education (*State Education*), and the population of each state (*State Population*).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Panel A** | | | | **Panel B** | | |
|  | (1) | (2) | (3) | (4) | (1) | (2) | (3) |
|  | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread |
| *Audit rate t-1* | -.015\*\* | -.022\*\*\* | -.02\*\*\* | -.02\*\*\* | -.021\*\*\* | -.015\*\* | -.015\*\* |
|  | (-2.401) | (-3.754) | (-3.163) | (-3.199) | (-3.159) | (-2.196) | (-2.218) |
| *Equity t-1* | -.122\*\*\* |  |  |  |  |  |  |
|  | (-6.612) |  |  |  |  |  |  |
| *Sales t-1* |  | -.096\*\*\* |  |  |  |  |  |
|  |  | (-6.602) |  |  |  |  |  |
| *Firm Size t-1* |  |  | -.814 | -.122\*\*\* |  |  |  |
|  |  |  | (-1.484) | (-4.586) |  |  |  |
| *(Firm Size t-1)2* |  |  | .081 |  |  |  |  |
|  |  |  | (1.184) |  |  |  |  |
| *(Firm Size t-1)3* |  |  | -.003 |  |  |  |  |
|  |  |  | (-1.118) |  |  |  |  |
| *IRS Offices State* |  |  |  |  | .028 | .204\*\* | .123 |
|  |  |  |  |  | (.763) | (2.464) | (1.297) |
| *Audit rate t-1\*IRS Offices State* |  |  |  |  |  | -.006\*\* | -.005\*\* |
|  |  |  |  |  |  | (-2.219) | (-2.031) |
| *State Unemployment t-1* |  |  |  |  | -.025\* | -.024\* | -.033\*\* |
|  |  |  |  |  | (-1.926) | (-1.848) | (-2.539) |
| *State Education  t-1* |  |  |  |  | .703 | .754 | 1.073 |
|  |  |  |  |  | (1.089) | (1.167) | (1.59) |
| *State Income Cap  t-1* |  |  |  |  | -.604\*\* | -.616\*\* | -.753\*\*\* |
|  |  |  |  |  | (-2.424) | (-2.471) | (-2.925) |
| *State Population  t-1* |  |  |  |  |  |  | .067\*\* |
|  |  |  |  |  |  |  | (2.066) |
| Constant | 6.578\*\*\* | 6.729\*\*\* | 8.849\*\*\* | 6.937\*\*\* | 13.253\*\*\* | 13.195\*\*\* | 13.554\*\*\* |
|  | (25.789) | (31.32) | (6.085) | (23.212) | (5.324) | (5.298) | (5.438) |
| Observations | 6504 | 6741 | 6951 | 6951 | 6951 | 6951 | 6951 |
| R-squared | .637 | .618 | .626 | .625 | .63 | .631 | .632 |
| Control Variables | Y | Y | Y | Y | Y | Y | Y |
| Loan purpose & type FE | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | N | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | N | Y | Y | Y |
| Size class trends | N | N | N | Y | N | N | N |

Significance at the 10%, 5%, and the 1% level is represented by \*, \*\*, and \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering.

**Table IA.4.** The conditioning effect of lending relationships on the association between IRS monitoring and the cost of bank loans (hypotheses *H.2A* vs. *H.2B*) – Alternative IRS monitoring measures. The Table presents the results from regressing bank loan spreads on the interaction between alternative IRS monitoring measures and relationship lending variables after controlling for firm-level and loan-level characteristics. Regressions are based on OLSs and include time effects. Therefore, the main effect of the alternative IRS monitoring measures drops from the models as these measures display only yearly variation. However, the interaction terms between these alternative measures of IRS monitoring and the lending relationships variables can be identified in the presence of time effects.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|  | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread |
| *RIA t* | .226\*\* | .223\*\* | .221\*\* | .02 | -.039 | .127 | -.255 |
|  | (2.324) | (2.224) | (2.182) | (.355) | (-.994) | (1.585) | (-1.315) |
| *IRS Revenue agents t-1 \*RIA t* | -.068\*\*\* |  |  |  |  |  |  |
|  | (-2.949) |  |  |  |  |  |  |
| *IRS Employees t-1\*RIA t* |  | -.009\*\*\* |  |  |  |  |  |
|  |  | (-2.805) |  |  |  |  |  |
| *IRS Criminal investigators t-1\*RIA t* |  |  | -.296\*\*\* |  |  |  |  |
|  |  |  | (-2.769) |  |  |  |  |
| *IRS Fraud penalties t-1* \**RIA t* |  |  |  | -.853 |  |  |  |
|  |  |  |  | (-1.6) |  |  |  |
| *IRS Negligence penalties t-1\*RIA t* |  |  |  |  | -.129 |  |  |
|  |  |  |  |  | (-.695) |  |  |
| *IRS Criminal referrals t-1\*RIA t* |  |  |  |  |  | -.201\*\* |  |
|  |  |  |  |  |  | (-2.44) |  |
| *IRS Criminal prosecutions t-1\*RIA t* |  |  |  |  |  |  | .03 |
|  |  |  |  |  |  |  | (1.153) |
| Constant | 6.073\*\*\* | 5.638\*\*\* | 5.76\*\*\* | 6.253\*\*\* | 6.302\*\*\* | 6.183\*\*\* | 6.346\*\*\* |
|  | (13.661) | (10.159) | (10.308) | (24.965) | (27.974) | (20.411) | (28.452) |
| Observations | 3218 | 3218 | 3218 | 3218 | 3218 | 3218 | 3218 |
| R-squared | .636 | .636 | .636 | .635 | .634 | .635 | .634 |
| Control Variables | Y | Y | Y | Y | Y | Y | Y |
| Loan purpose & type FE | Y | Y | Y | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y | Y | Y | Y |
| Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering. | | | | | | | |

**Table IA.5.** The conditioning effect of lending relationships on the association between IRS monitoring and the cost of bank loans (hypotheses *H.2A* vs. *H.2B*) – Alternative IRS monitoring measures. The Table presents the results from regressing bank loan spreads on the interaction between alternative IRS monitoring measures and relationship lending variables after controlling for firm-level and loan-level characteristics. Regressions are based on OLSs and include time effects. Therefore, the main effect of the alternative IRS monitoring measures drops from the models as these measures display only yearly variation. However, the interaction terms between these alternative measures of IRS monitoring and the lending relationships variables can be identified in the presence of time effects.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|  | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread |
| *RIA t* | .226\*\* | .223\*\* | .221\*\* | .02 | -.039 | .127 | -.255 |
|  | (2.324) | (2.224) | (2.182) | (.355) | (-.994) | (1.585) | (-1.315) |
| *IRS Revenue agents t-1 \*RIA t* | -.068\*\*\* |  |  |  |  |  |  |
|  | (-2.949) |  |  |  |  |  |  |
| *IRS Employees t-1\*RIA t* |  | -.009\*\*\* |  |  |  |  |  |
|  |  | (-2.805) |  |  |  |  |  |
| *IRS Criminal investigators t-1\*RIA t* |  |  | -.296\*\*\* |  |  |  |  |
|  |  |  | (-2.769) |  |  |  |  |
| *IRS Fraud penalties t-1* \**RIA t* |  |  |  | -.853 |  |  |  |
|  |  |  |  | (-1.6) |  |  |  |
| *IRS Negligence penalties t-1\*RIA t* |  |  |  |  | -.129 |  |  |
|  |  |  |  |  | (-.695) |  |  |
| *IRS Criminal referrals t-1\*RIA t* |  |  |  |  |  | -.201\*\* |  |
|  |  |  |  |  |  | (-2.44) |  |
| *IRS Criminal prosecutions t-1\*RIA t* |  |  |  |  |  |  | .03 |
|  |  |  |  |  |  |  | (1.153) |
| Constant | 6.073\*\*\* | 5.638\*\*\* | 5.76\*\*\* | 6.253\*\*\* | 6.302\*\*\* | 6.183\*\*\* | 6.346\*\*\* |
|  | (13.661) | (10.159) | (10.308) | (24.965) | (27.974) | (20.411) | (28.452) |
| Observations | 3218 | 3218 | 3218 | 3218 | 3218 | 3218 | 3218 |
| R-squared | .636 | .636 | .636 | .635 | .634 | .635 | .634 |
| Control Variables | Y | Y | Y | Y | Y | Y | Y |
| Loan purpose & type FE | Y | Y | Y | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y | Y | Y | Y |
| Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively. T-statistics are in parentheses, and we use within firm-clustering. | | | | | | | |

**Table IA.6** The effect of IRS monitoring the cost of bank loans - controlling for additional tax avoidance measures. This Table presents the results from regressing bank loan spreads on the Internal Revenue Service (IRS) audit rates after controlling for firm-level, loan-level characteristics (all models) and a number of tax avoidance measures (ROLL CASH ETR, SUM CASH ETR, GAAP ETR, ROLL GAAP ETR, SUM GAAP ETR, BT, and SHELTER). Table IA.1 provides the definitions and calculations for the additional tax avoidance variables.

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|  | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread | Loan  spread |
| *Audit rate t-1* | -.02\*\*\* | -.023\*\*\* | -.02\*\*\* | -.021\*\*\* | -.021\*\*\* | -.026\* | -.026\* |
|  | (-3.333) | (-3.677) | (-3.298) | (-3.269) | (-3.27) | (-1.717) | (-1.703) |
| *ROLL CASH ETR t-1* | .45\*\*\* |  |  |  |  |  |  |
|  | (6.363) |  |  |  |  |  |  |
| *SUM CASH ETR t-1* |  | .892\*\*\* |  |  |  |  |  |
|  |  | (10.979) |  |  |  |  |  |
| *GAAP ETR t-1* |  |  | .905\*\*\* |  |  |  |  |
|  |  |  | (10.463) |  |  |  |  |
| *ROLL GAAP ETR t-1* |  |  |  | .391\*\*\* |  |  |  |
|  |  |  |  | (4.605) |  |  |  |
| *SUM GAAP ETR t-1* |  |  |  |  | .389\*\*\* |  |  |
|  |  |  |  |  | (4.583) |  |  |
| *BT t-1* |  |  |  |  |  | .125\*\* |  |
|  |  |  |  |  |  | (2.271) |  |
| *SHELTER t-1* |  |  |  |  |  |  | .019\*\*\* |
|  |  |  |  |  |  |  | (2.971) |
| Constant | 7.043\*\*\* | 7.027\*\*\* | 6.987\*\*\* | 7.007\*\*\* | 7.008\*\*\* | 7.357\*\*\* | 7.413\*\*\* |
|  | (28.7) | (28.701) | (28.857) | (28.259) | (28.26) | (14.054) | (14.157) |
| Observations | 6951 | 6951 | 6951 | 6951 | 6951 | 2333 | 2333 |
| R-squared | .626 | .642 | .636 | .624 | .624 | .722 | .722 |
| Control variables | Y | Y | Y | Y | Y | Y | Y |
| Loan purpose & type FE | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y | Y | Y | Y |

**Table IA.7** The effect of IRS monitoring on the cost of bank loans - alterative clustering of standard errors. This Table presents the results from regressing bank loan spreads on the IRS audit rate after controlling for firm-level and loan-level characteristics using an alternative clustering of standard errors.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Loan  Spread | Loan  Spread | Loan  Spread | Loan  Spread |
| *Audit rate t-1* | -.02\*\* | -.018\*\* | -.02\*\*\* | -.018\*\*\* |
|  | (-2.405) | (-2.154) | (-3.283) | (-2.966) |
| *RIA t* |  | .23\*\*\* |  | .23\*\*\* |
|  |  | (3.359) |  | (3.052) |
| *Audit rate t-1*\* RIA t |  | -.008\*\*\* |  | -.008\*\*\* |
|  |  | (-3.419) |  | (-3.239) |
| Constant | 7\*\*\* | 6.94\*\*\* | 7\*\*\* | 6.94\*\*\* |
|  | (26.829) | (26.08) | (29.47) | (29.38) |
| Observations | 6951 | 6951 | 6951 | 6951 |
| R-squared | .625 | .626 | .625 | .626 |
| Loan purpose & type FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y |
| Clustering | size class-year | size class-year | bank-firm | bank-firm |

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively.

**Table IA.8** Other robustness analysis- This Table presents the results from regressing bank loan spreads on IRS audit rate after controlling for firm and loan-level characteristics. Note: the variable that captures the state-level business tax climate (*SBTX*) is available from 2003 onwards.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Loan  Spread | Loan  Spread | Loan  Spread | Loan  Spread |
| *Audit rate t-1* | -.039\*\* | -.021\*\*\* |  | -.019\*\*\* |
|  | (-2.025) | (-3.318) |  | (-2.729) |
| *Syndicate size t* |  | -.038\* |  |  |
|  |  | (-1.657) |  |  |
| *Audit rate t* |  |  | -.006\*\* |  |
|  |  |  | (-2.099) |  |
| *SBTX t-1* |  |  |  | -.003\*\* |
|  |  |  |  | (-2.37) |
| Constant | 7.468\*\*\* | 7.026\*\*\* | 6.568\*\*\* | 7.088\*\*\* |
|  | (12.324) | (28.532) | (35.033) | (26.617) |
| Observations | 649 | 6951 | 6951 | 4024 |
| R-squared | .668 | .626 | .625 | .645 |
| Loan purpose & type FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Lead Lender FE | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y |
| Size class FE | Y | Y | Y | Y |

Significance at the 10%, 5%, or the 1% level is represented by \*, \*\*, or \*\*\*, respectively.

1. The start in 1993 reflects the availability of data on IRS tax enforcement. [↑](#footnote-ref-1)
2. We discuss in detail the potential of these two instruments to satisfy the inclusion and exclusion restrictions in subsection 4.1.1 of the manuscript. [↑](#footnote-ref-2)
3. Although, Gallemore and Jacob (2020) focus on SMEs lending, where information asymmetry is more severe in comparison with larger firms, it is plausible that private lenders could value IRS monitoring for lending to larger firms. For example, Hanlon et al. (2014) show that IRS monitoring improves the quality of financial reporting from comparatively larger Compustat firms, while Mazumdar and Sengupta (2005) show that the quality of financial reporting enhances the access to private debt for such firms. [↑](#footnote-ref-3)
4. We do recognize that IRS monitoring might be more useful for public providers of external financing in comparison with private lenders. Banks possess superior access to private information on borrowers and stronger monitoring ability (Bharath et al. 2008; Shevlin et al. 2020). We discuss this distinction theoretically and provide the results of relevant empirical tests in subsection 4.2.2 of the manuscript. [↑](#footnote-ref-4)
5. These studies (Schenone 2010; Cahn et al. 2021; Saidi and Zaldokas 2021) show that positive information shocks decrease relationship banks' information advantage and, thus, increase borrowers' bargaining power. However, other studies examine how a decrease in the bargaining power of borrowers enables relationship banks to extract information rents. For example, Chen et al. (2020) show that stock market illiquidity enables banks to charge higher loan prices to their relationship borrowers. The authors posit that this finding is consistent with the decreased bargaining power channel. All in all, several studies use the setting of lending relationships to provide evidence of the borrowers' bargaining power channel on the cost of bank loans. [↑](#footnote-ref-5)
6. We follow other studies and perform our analysis at the loan facility level and not at the loan package level (e.g., Hasan et al. 2014; Hasan et al. 2017). Each loan package could contain more than one loan facility. Two loan facilities, even when they are part of the same loan package, could have different sizes, maturities, and types. Therefore, ignoring the differences between loan facilities could introduce estimation bias. [↑](#footnote-ref-6)
7. Our analysis starts from 1993 as IRS tax enforcement data became available in 1992, and we use the values of lagged audit rates in our regressions. [↑](#footnote-ref-7)
8. There are eight size classes based on the level of firms’ total assets. These are the following: more than $250 million, $100-$250 million, $50-$100 million, $10-$50 million, $5-$10 million, $1-$5 million, $0.25-$1 million and $0-$0.25 million. Note that our sample uses observations from the seven biggest categories. This is because we could not find any firm in the smallest size class of $0-$0.25 million that had obtained a syndicated loan in the period under study. [↑](#footnote-ref-8)
9. Following Chakraborty et al. (2018), we consider that a lending relationship is established between the lead bank of the syndicate and a borrowing firm. Lead banks are the key lending institutions in syndicated loans as they determine the price of the loan and the other non-price terms (e.g., maturity and size). Lead banks are also responsible for the screening and monitoring of the borrowing firm (Ivashina 2009; Prilmeier 2017; Gustafson et al. 2020). To identify the lead bank of a syndicated loan, we follow the method used by Sufi (2007). [↑](#footnote-ref-9)
10. We use the natural log of the loan spread as the dependent variable that follows the other studies on the determinants of the cost of bank loans (see, e.g., Lin et al. 2018). [↑](#footnote-ref-10)
11. Note that in these estimations we do not have time effects. This is because time effects could have perfect collinearity with the IRS staffing measures that display only yearly variation. [↑](#footnote-ref-11)
12. We source data to construct all the additional tax avoidance variables from Compustat. [↑](#footnote-ref-12)
13. One concern with the use of the GAAP effective tax rate as a measure of tax avoidance is that it does not capture strategies of tax avoidance that defer cash taxes. This is due to the offsetting effect of an increase in deferred tax expense to the reduction in the current tax expense (Hanlon and Heitzman 2010; Cen et al. 2017). For this reason, we chose to use the cash effective tax rate as a tax avoidance control in the baseline model. [↑](#footnote-ref-13)