HONG KONG INSTITUTE FOR MONETARY RESEARCH

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HKIMR Working Paper No.01/2016

January 2016

Hong Kong Institute for Monetary Research
香港金融研究中心
(a company incorporated with limited liability)

Do Banks Extract Informational Rents through Collateral?*

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January 2016

Abstract

This paper investigates if relationship lending and bank market concentration permit informational rent extraction through collateral. We use equity IPOs as informational shocks that erode rent seeking opportunities. Using unique loan data from China, we find collateral incidence increases with relationship intensity and bank market concentration for pre-IPO loans, while these effects are moderated post-IPO. We further discover after an IPO, rent extraction is moderated for safe firms but intensified for risky firms. These results are not driven by differences or changes in financial risks. Ours is the first investigation on collateral determinants for China with loan-level data.

JEL Classification: G21; L11.

Key Words: Informational rents; collateral; relationship lending; market structure; IPOs; China.

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* We thank Yue Ma, Jun Qian, Chen Lin, Dong He, Hongyi Chen, Michael Chui, Hao Zhou, Hong Zhang, and the participants at the 2015 China conference of the Hong Kong Institute for Monetary Research (HKIMR), 7th IFABS internatinal conference, PBC School of Finance at Tsinghua University, Fudan University, People's bank of China (Shanghai), internal seminars in the BIS and HKIMR for very constructive comments and helpful suggestions. Bing Xu thanks the hospitality of HKIMR during his visit. All remaining errors are ours.

The views expressed in this paper are the authors' and do not necessarily reflect those of the Hong Kong Institute for Monetary Research or the Bank for International Settlements.

1. Introduction

Banks accumulate proprietary information about borrowers through lending relationships, which create informational asymmetries between "inside" banks that are already lending to a firm and "outside" banks that currently are not (Santos and Winton, 2008). Besides relationship lending, recent theoretical studies have highlighted that concentrated bank market structure also facilitates information asymmetry among lenders (e.g. Dell'Ariccia et al., 1999; Dell'Ariccia, 2001). As informed banks accumulate inside information about their borrowers, the adverse selection problem facing non-lenders grows. Consequently, borrowers face higher switching costs and inside banks are in a position to request harsher loan conditions than would prevail were all banks symmetrically informed, in other words, inside banks can charge informational rent. Empirical validation of informational rent extraction theory mainly focus on lending rates (see e.g. Hale and Santos, 2009; Schenone, 2010), and non-price terms are largely unexplored. Furthermore, existing studies mainly investigate if relationship lending facilitates informational rent extraction (Sharpe, 1990; Rajan, 1992), while the possibility that concentrated bank market structure can play a similar role has not been empirically validated. In this paper, we intend to fill this gap by examining if inside information, obtained through both relationship lending and concentrated market structure, allows banks to extract informational rents through collateral. In so doing, we use equity IPOs of borrowers as information releasing shocks that erode information based rent seeking opportunities. Using a unique hand-collected loan level dataset from China, our evidence suggests proprietary information does allow rent extraction through collateral for pre-IPO loans, while this effect is greatly moderated for post-IPO loans.

Why would banks be incentivized to charge more collateral than is justified by borrower risks? The theoretical models of collateral provide a few insights. Lenders often demand collateral because it: mitigates ex-post borrower moral hazard problems (e.g. Boot et al., 1991), signals the credit quality of borrowers (Bester, 1985; Besanko and Thakor, 1987) and minimizes loan losses when borrowers default (Berger and Udell, 1990). These features imply that collateral is valuable to banks not only in the case of default, but at all stages of the lending process. Collateral is particularly important in markets where banks lack sufficient tools or expertise to price credit risks, or are prevented from doing so because of price regulations. In the case of China, an additional incentive to request collateral is to reduce the personal risks facing by loan officers, as the loan officer responsibility system introduced in 2002 holds individual loan officers accountable for bad loans (Qian et al., 2015). In practice, collateral is widely imposed in bank lending markets across a broad range of countries in general and in emerging market economies in particular (see e.g. Menkhoff et al., 2006).[1] In our view, the important role of collateral warrants an in-depth empirical analysis of its potential use in charging rents from borrowers.

Informational rent depends crucially on the existence of informational asymmetry between lenders and non-lenders (Schenone, 2010). The role of relationship lending in facilitating this information asymmetry has been well established (Sharpe, 1990; Rajan, 1992). What's far less obvious is that a similar role can be played by concentrated bank market structure. We discuss briefly a sequence of theoretical advances that have related market structure to the information distribution among lenders, which in turn interact with banks' strategic behavior in determining lending policies and standards (e.g. Dell'Ariccia, 2001; Marquez, 2002; Dell'Ariccia and Marquez, 2006; Hauswald and Marquez, 2006).[2] First, information extraction is likely to be less effective in markets composed of many small banks instead of a few large banks (Marquez, 2002). Concentrated markets also allow for better protection of proprietary information, preventing spill-overs to competitors, as banks with larger market shares have higher incentives and capacity to maintain this informational advantage. Therefore, concentrated lending markets not only consolidate market shares, but also protect proprietary information about borrowers. Second, different market structures associated with different implied levels of competition, may also affect the incentive of banks to accumulate information. Increased competition reduces the rent that banks can extract, reducing the incentive to generate information through credit evaluation (Hauswald and Marquez, 2006). More outside borrowing options for firms in less concentrated markets

[1] According to the World Bank Enterprise Surveys, collateral is required in 75% of the loans taken out worldwide, and the lack of collateral constitutes one of the primary obstacles to external finance. See http://www.enterprisesurveys.org/

[2] We restrict ourselves to theories that relate bank market structure to information asymmetry among lenders. Other theories (not crucially related to information asymmetry among lenders) also provide predictions. For instance, Manove et al. (2001) propose a "lazy bank" model in which banks choose between screening the borrower or ask for collateral. They argue that intensified competition would favor bank laziness by reducing screening and requesting more collateral. Hainz et al. (2013) propose that bank competition makes screening more effective. Hence, collateral – an alternative to screening – is less common in competitive markets. Inderst and Muller (2007) develop an inside lenders'–based model of collateral which does not assume the existence of information asymmetries on the borrower's side. These authors predict that the incidence of collateral is higher in more competitive markets.

also inhibit the (re)usability of information and diminishes its value, as firms can switch banks easily, therefore banks are incentivized to invest less in information production (Boot and Thakor, 2010; Chan et al., 1986; Berlin and Mester, 1999).[3] Third, because of limited outside options, firms are likely to borrow more often from the same lenders in concentrated markets, which allow these banks to accumulate more private information. Lastly, consolidation of proprietary information in concentrated markets deters the entry of new banks, as new entrant banks face larger adverse selection problems. Thus, information consolidation further increases the degree of market concentration and reinforces the information monopoly of incumbent banks (Dell'Ariccia et al., 1999; Dell'Ariccia, 2001). To sum up, these arguments suggest that concentrated markets allow for a more efficient extraction of private information and provide stronger incentives to obtain it; offer better protection from this information spilling over to competitors (outside banks); and deters competitors from entering the market which reinforces any information monopolies. A straightforward implication is that concentrated markets may also facilitate informational rent extraction. The role of concentrated market structure in extracting informational rents, however, receives very little attention in the empirical literature.

One of the main difficulties facing this research is isolating informational rent extraction from alternative theories that predict the same empirical results. In terms of relationship lending, at least three theories other than informational rent extraction can predict the same positive impact of relationship lending on collateral. Longhofer and Santos (2000) suggest that pledging collateral improves the seniority of a bank's debt claims, which incentivizes the bank to engage in ongoing, long-term, valuable lending relationships. Borrowers benefit from this, because bank seniority induces relationship lenders to provide support to distressed borrowers, as the senior debtors benefit the most from a turn-around of the firm.[4] Dewatripont and Maskin (1995) highlight another potential cost of relationship lending which hinges on the observation that relationship lenders have an incentive to extend further credit in the hope of recovering loans granted previously when a borrower is in financial stress. Anticipating the ex-post realization of this "soft budget constraint", the borrower is not sufficiently incentivized to make an effort ex-ante to prevent such an adverse outcome. Collateral is therefore more likely to be

[3] If increased competition makes differentiation from outside banks more important, inside banks should acquire information more intensely (Boot and Thakor, 2000 and 2010).

[4] See Elsas and Krahen (2000) for further discussion and empirical testing of this argument. Their results indicate that house banks require more collateral as compensation for their active involvement in the restructuring of distressed borrowers.

requested when a bank-firm relationship intensifies to solve this soft budget constraint problem (Boot, 2000). Both theories suggest that, as borrower risk increases, relationship lenders are more likely to request collateral because the likelihood of engaging in a future rescue increases or the soft budget constraint problem intensifies. Lastly, Menkhoff et al. (2006) suggests that banks may extend relationship length (intensity) to minimize the per unit fixed costs associated with evaluating and monitoring collateral ("cost minimization incentive"), which *de facto* produces a positive correlation between collateral and relationship duration (intensity). In terms of bank market concentration, the positive impact of market concentration on collateral may also be explained by bank market power, i.e. banks can exploit their sheer market power in concentrated markets by imposing more stringent collateral requirements (Hainz, 2003; Berlin and Butler, 2002).

Informational rent extraction depends crucially on information asymmetries among inside and outside lenders, while this precondition is not conducive to the core argument in alternative theories. This observation leads to an intuitive identification strategy: if inside banks extract informational rents through collateral, their ability to do so should be moderated after some exogenous shock that reduces information asymmetry between inside and outside banks. If this moderated effect is not validated empirically, one can reject the informational rent hypothesis and attribute the higher incidence of collateral of inside banks to competing theories. To this end, we follow Schenone (2010) and introduce equity IPOs of borrowing firms as such a shock[5]. Equity IPOs are a credible channel to disseminate previously proprietary information through compulsory financial reporting, public auditing, financial analysts' research and movements in stock prices. As this new information is made public to all banks, the informational monopoly position of inside banks is eroded, and the adverse selection problem facing outside banks is alleviated, leading to a lesser likelihood of rent extraction for post-IPO loans than for pre-IPO loans. One crucial part of the methodology is to control for shifts in firm risks around IPOs or differences in risks between listed and unlisted firms, so that any changes in behaviour can be attributed to changes in information asymmetries, instead of differences in credit risks. We control for this by introducing a large amount of information on firm risk characteristics both before and after the IPO, and later perform additional robustness tests, which are discussed shortly. To the best of our

[5] A similar approach is taken by Santos and Winton (2008) and Hale and Santos (2009) using corporate bond IPOs as such shock. These papers together with Schenone (2010) investigate informational rent extraction through lending rates.

knowledge, ours is the first paper to use equity IPOs to identify whether banks charge informational rents through collateral.

Unlike most studies that employ data for advanced economies, our testing ground is China. Chinese bank lending markets are ideal for our research for several reasons. First, China is a bank-based economy that for many years has been characterized by strict interest rate controls, many of which remain in place as of today. This suggests that banks have less discretion in setting prices compared to their counterparts in advanced economies, making rent extraction through collateral an attractive alternative. Second, lending markets in China are relatively segmented and offer significant variation across regions and time. This feature allows us to test if collateral requirements vary with the information configurations embedded in regional bank market structures. Third, the particular features of equity IPO regulations and procedures in China make it a valid choice as an exogenous informational shock. Firms might expect to go public at some point, but the exact timing of an IPO depends on the approval by the China Securities Regulatory Commission (hereafter the CSRC), which is unpredictable and exogenous to both banks and firms, suggesting that adjustments of loan contract terms prior to an IPO are hardly economically viable. We manually collect information on loans taken out by firms listed at the Shenzhen Stock Exchange, both before and after their listing. Focusing on a sample of firms that have completed their IPOs will bias against finding informational rent extraction because these firms are generally large, and information about these firms is more symmetrically distributed among lenders.[6]

We report five main findings. First, all else equal, a high relationship intensity and concentrated market structure are associated with a higher incidence of collateral, and these effects are less pronounced for transparent firms. Furthermore, we find that there is a boundary transparency level beyond which informational rent extraction becomes infeasible.

[6] Berger et al. (2011) point out that testing informational rents related to relationship lending by using a sample of small firms could bias the results towards a positive coefficient for the relationship lending variable, because small and opaque firms are precisely the ones required to pledge collateral (according to “observed-risk” hypothesis), and banks tend to use relationship lending to deal with these informational opaque firms.

Second, when applying IPOs as an informational shock, we find for pre-IPO originated loans the likelihood of collateralization increases with relationship intensity, while this effect is greatly moderated for post-IPO loans. In some specifications, it is no longer significant in predicting collateral incidence. In contrast to Schenone (2010), which shows that the lending spread is decreasing with relationship intensity once a borrower is listed, we do not find a similar pattern for collateral. The relatively low degree of competitiveness in the Chinese banking sector relative to that in the United States might explain this result.[7]

Third, the likelihood of collateral increases with the degree of market concentration both before and after the IPO, but the effect is moderated for post-IPO loans. This finding supports the hypothesis that concentrated markets facilitate information asymmetries among lenders and hence are associated with a higher likelihood of rent extraction through collateral. Unlike relationship intensity, the impact of market structure on collateral remains significantly positive and economically large for post-IPO loans. This lends some support to the idea that pure market power stemming from concentrated market structures may allow banks to charge rents, regardless of the level of information asymmetries existing among banks (Hainz, 2003; Berlin and Butler, 2002).

Fourth, using a novel measure of firm risk, that is whether a firm’s first IPO application was rejected by the CSRC, we find once information about a firm’s risk is made public after IPO, rent extraction through collateral is moderated for safe firms but intensified for risky firms. This result is in line with the theoretical prediction of Rajan (1992) that informed banks are more able to extract rents from risky firms than safer ones. Our finding further complements Hale and Santos (2009) who report similar results with lending rates.

Finally, we find that firms with higher credit risk are more likely to pledge collateral, a result consistent with the “observed-risk” hypothesis (e.g. Boot et al., 1991; Boot and Thakor, 1994). Furthermore, our

[7] If the relationship lender is facing limited competition (for instance due to restrictions on business scope, geographical restrictions on branch expansion and funding limitations for potential competitors), this bank will not share rents (surpluses) with borrowers or soften its lending standards relative to transaction based lenders simply because its informational advantage is diminished after its IPO.

evidence shows private firms are much more likely to pledge collateral compared with state-owned firms, adding to previous findings that private firms in China are charged with higher lending rates in a state-dominant banking system (Cull and Xu, 2003; Allen et al., 2005). To the best of our knowledge, ours is the first paper to investigate collateral in Chinese banking markets with loan-level data[8].

Our findings are largely consistent with the informational rent extraction hypothesis, subject to two important caveats: firstly, our results could be justified by alternative theories and, secondly, the potential endogeneity issue of key variables in our equations could bias our results. We proceed by contrasting the informational rent hypothesis with three alternative explanations. Firstly, both "bank seniority theory" and "soft-budget constraint theory" highlight the possibility that relationship lenders require less collateral for financially healthier firms. If listed firms are financially sounder than unlisted firms and our framework has not fully controlled this difference, the moderated effect of relationship lending on collateral for post-IPO loans could be explained by these theories. We apply three tests to address this concern. First we investigate if listed firms are financially healthier than unlisted ones by comparing observed risk proxies. We do not find supporting evidence either in our own sample or from previous studies investigating this issue. Then, to address potential selection bias caused by observables, we employ the propensity score matching method to generate a matched sample of loans that are "identical" in every aspect, expect for the borrower's listing status. We re-estimate the baseline model on this matched sample. Unreported results on this matched sample remain quantitatively unchanged. Lastly we address unobserved risk differences using a recursive bivariate probit model with instrumental variable, which are discussed below.

The second alternative explanation is related to selection effects in credit quality: suppose the relationship dependent listed firms that obtain loans are on average safer than relationship dependent unlisted firms, while the relationship non-dependent listed firms that obtain loans are on average riskier than relationship non-dependent unlisted firms. This selection effect could explain the moderated effect

[8] Very few studies have investigated the determinants of collateral in China. Notable exceptions include Firth et al. (2012) and Chen et al. (2013). However, none of these studies investigate the determinants of collateral at the *loan-level* or pay attention to the importance of relationship lending and market structure for the incidence of collateral, as well as how changes in information asymmetries among lenders may affect these linkages.

of relationship lending on collateral for post-IPO loans. We perform difference-in-difference tests for observed risk proxies broken down by whether a firm is relationship dependent and whether the loan is borrowed after an IPO. We do not find evidence to support this explanation. As a further robustness test, we employ the propensity score matching method to find matching firms that differ only in their relationship dependency within both pre- and post-IPO loans samples, and compare the average treatment effects of relationship dependency on collateral between these two samples. In this way, we can discard the alternative explanation, that some unobserved shifts in firm-risk or heterogeneous dynamics of risk shifting due to the IPO, drive our results because we compare matching firms within both pre- and post-IPO samples. For our pre-IPO sample, we find that relationship dependent firms are on average 10-12% more likely to pledge collateral than non-dependent firms, while no such difference exists for our post-IPO sample (Internet Appendix A).

The third alternative explanation is that banks exchange better loan conditions (lower likelihood of collateral) for corporate bond underwriting business[9]. This behavior could also result in a moderated effect of relationship lending on collateral for post-IPO loans, given that most of the firms issue bond IPOs after equity IPOs, and relationship lenders are involved intensively on bond IPOs. To isolate this alternative explanation, we re-estimate the baseline model on samples of loans that were originated before bond IPOs. We find this explanation cannot dismiss the rent-extraction hypothesis.

Our previous framework relies on an important assumption that IPO and relationship lending variables are exogenous. In reality, both could be endogenous due to omitted variables thereby generating biased estimation. For instance, there could be uncontrolled variables that improve a firm’s chances of being listed and at the same time reduces collateral requirement. Therefore the moderated effect of relationship lending on collateral for post-IPO loans could be a result of an unobserved higher credit quality of listed firms instead of less information asymmetry. A similar endogeneity issue applies to

[9] If firms issued for the first time in public corporate bond markets (e.g. bond IPO) prior to their equity IPO, the latter may not serve as the sole significant event of information equalization, as corporate bond IPOs also require extensive information disclosure. This issue is not a major concern in our sample, because only three firms issued corporate bonds before their equity IPO, which does not affect our choice of equity IPOs as the main information disclosure events. Another issue is that commercial banks may promise favorable loan contract terms in exchange for underwriting a firm’s equity IPO, which can lead to alternative explanations of our results (see discussion in Schenone, 2010). This concern is alleviated in China, because equity IPOs are strictly underwritten by security firms instead of commercial banks.

relationship lending. Firms with bad credit quality (unobserved to the econometrician but known to all banks) could be more likely to borrow from relationship lenders and at the same time be subject to higher collateral requirement. The higher likelihood of collateral for relationship loans might simply reflect unobserved poor credit quality instead of informational hold-up. To address these concerns, we employ recursive bivariate probit models to test whether listing status or relationship dependency is endogenous, and if our conclusion changes after controlling for the endogeneity of these respective variables. In both cases, we find appropriate instrumental variables so the identification does not rely solely on the non-linearality of functional form. In so doing, we derive novel instrumental variables for IPOs from exogenous policy shocks such as CSRC IPO suspensions. Our main results hold after controlling for the endogeneity of IPOs or relationship lending.

In addition, we perform several tests to investigate if our results are robust to the inclusion of firm fixed effects; endogeneity of other loan contract terms (by both removing these variables and estimating IV probit model); and to alternative samples. In a set of unreported robustness tests, we investigate if our results hold using an alternative relationship lending measure, and controlling for regional legal and institutional variables in determining collateral. These tests do not change our results.

The remainder of the paper is organized as follows. Section 2 details our methodology and data. Section 3 presents the main empirical results. Section 4 checks our conclusions with alternative theories. Section 5 controls for a possible endogeneity relating to IPOs or relationship lending. Section 6 reports the results of further robustness tests. Finally, Section 7 concludes. Additional results can be found in an Internet Appendix to this paper.

2. Methodology and data

2.1. Methodology

The methodology of the main analysis contains four parts. Firstly, we investigate if the likelihood of collateral increases with relationship lending and market concentration, after controlling for a broad range of other determinants. The second part attempts to find evidence that the increasing likelihood of collateral is at least partially due to information asymmetries between inside and outside banks. To this end, we test if the effects of relationship lending and market concentration on collateral are less pronounced for transparent firms, using various information transparency proxies. The third part investigates if informational rent extraction is moderated for post-IPOs loans relative to pre-IPOs loans. Finally, we investigate if this moderated effect for post-IPOs loans varies with firm risk. We discuss the methodologies related to alternative explanations, the possible endogeneity of key variables, and further robustness tests in Sections 4, Section5, Section 6, respectively.

2.1.1. Relationship lending and market structure as determinants of collateral incidence

We start by testing whether relationship lending and market structure are positively correlated with collateral in a cross-sectional setting. As discussed in the Introduction, a positive correlation between relationship intensity and collateral does not automatically imply “informational rent extraction”, because at least three competing theories predict the same result (e.g. “bank seniority”, “soft budget constraint” and “cost minimization incentive”). In contrast, a negative correlation would support the “information accumulation” view, which considers relationship lending and collateral as substitutes (e.g. Petersen and Rajan, 1995; Berger and Udell, 1995; Bharath et al., 2011). With respect to market structure, a positive association with collateral would not unequivocally suggest informational rent extraction, but could also imply the use of sheer market power in concentrated markets (e.g. Hainz, 2003; Berlin and Butler, 2002). Hence, we postulate the following hypotheses:

H.1: If relationship lending is negatively related to collateral incidence, the information accumulation view holds. In contrast, a positive correlation would reject this.

H.2: Concentrated markets allow for a higher probability of collateral incidence, either because of the existence of informational monopolies, more market power or both.

To test these hypotheses, we estimate the following Probit model:

$$\mathrm{P(Collateral_{il})} = \mathrm{F}\Big(\beta_0 + \beta_1\mathrm{Sizeconcen_{il}} + \beta_2\mathrm{ACR4_{il}} + \textstyle\sum_{j=1}\sigma_j\mathrm{Relcontrols_{il}} + \rho\,\mathrm{IPO_{il}} + \sum_{j=1}\Phi_j\mathrm{FC_{il}} + \sum_{j=1}\theta_j\mathrm{LC_{il}} + \sum_{j=1}\gamma_j\mathrm{MC_{il}} + \sum_{j=1}\delta_j\mathrm{RC_{il}} + \sum_{j=1}\alpha_j\,\mathrm{FE_{il}}\Big) \quad (1)$$

where *i* indexes for firm, *l* for loan number, and *F(.)* is the cumulative distribution function of the standard normal distribution. The dependent variable $Collateral_{il}$ is a binary variable that equals one if loan *l* extended to firm *i* is collateralized and zero otherwise. IPO_{il} is a dummy equals 1 if a loan is issued after the borrower's IPO.

The strength of bank-firm relationships is traditionally measured by relationship duration, defined as the time difference between the first loan obtained and the current one (see e.g. Petersen and Rajan, 1995; Berger and Udell, 1995). As suggested in Schenone (2010), duration may not fully capture how dependent a firm is on its current lender or how "locked in" the firm is in the lending relationship. Hence, following Schenone (2010), we measure bank-firm relationships by the intensity with which the borrower turns to the same lender. This measure, which we call $Sizeconcen_{il}$, is defined as the amount of loans that firm *i* has borrowed from its current lender as a proportion of the total amount of loans which the firm has obtained prior to the current loan.[10] By definition, $Sizeconcen_{il}$ takes values of

[10] We employ another relationship measure, $Numconcen_{il}$, defined as the *number* of loans that firm *i* borrowed from its current lender as a proportion of the total *number* of loans which the firm obtained prior to the current loan, as a further robustness check. Our main results are not sensitive to this alternative measure (results are available on request). The implicit assumption of $Numconcen_{il}$ is that the inside lender is more informed than outside lenders if the firm borrows more times from its current lender, while the amounts borrowed are irrelevant for the accumulation of information. As it is expected that banks devote more efforts in

between zero and one. Borrower *i* is more dependent on the lender if $Sizeconcen_{il}$ is closer to one. This measure of relationship lending essentially takes into account the relative importance of a lender to the borrower, compared to other lenders. The next set of controls $Relcontrols_{il}$ accounts for additional features of relationship lending that can affect collateral incidence, including: the number of different lenders that firm *i* has borrowed from prior to the current loan, $Numlender_{il}$; whether the current loan is the first loan borrowed from the lender, $First_{il}$; and whether the current lender is different from the previous lender, $Switch_{il}$. $Numlender_{il}$ controls for the fact that the same value of $Sizeconcen_{il}$ does not preclude that a firm borrows from different number of banks. For instance, a loan associated with a value for $Sizeconcen_{il}$ of 0.5 can be the result of borrowing from two banks, with each accounting for half of the total loans, or borrowing from five banks, with the largest loan accounting for half of the total loans. The first loan from lender ($First_{il}$) might be subject to different collateral requirement. Finally, we include $Switch_{il}$ to control for the possibility that banks may condition their collateral requirements depending on whether they can provide subsequent loans, for instance to minimize the costs of collateral evaluation. For all these variables, loans originated by either the parent bank or a subsidiary are treated as loans from the same lender, since it is likely that the information available about the borrowing firm is shared within all subsidiaries.

Market structure is measured by the concentration ratio $ACR4_{il}$, which is defined as the share of total assets of the four largest banks as a percentage of the total assets of all banks in each province at the time of one semi-accounting year prior to the current loan.[11] We treat each province as a separate banking market.

The set of variables FC_{il} accounts for firm characteristics that are likely to affect collateral. These include the age of the firm in (log) months, Age_{il}; (log) total assets, $Size_{il}$; current assets over total assets, $Liquidity_{il}$; return on total assets, ROA_{il}; tangible assets over total assets, $Tangibility_{il}$; and firms ownership dummy FT_{il} (equals 1 if the Chinese State is the majority owner and 0 if majority ownership

assessing firms that borrow larger amounts and subsequently accumulate more firm-specific information if the loan is relatively large, $Sizeconcen_{il}$ is probably a more precise measure of firm-bank relationships.

[11] For our purposes, market structure should be measured at the regional level. The concentration ratio is the only measure available of regional market structures. Market structure is closely related to competition. For a discussion of bank competition in China and the results for various competition measures see Xu et al. (2013).

lies in the private sector). Following Berger and Udell (1990), we also control for the ratio of loan size relative to total outstanding debt (*Loanconcen*$_{il}$), as a higher ratio suggests more important loans, which are more likely to be collateralized. These variables are obtained from the semi-annual financial reports that are published the closest to the moment before the loan was originated. This procedure ensures that in our estimations, banks use the most recent publicly available accounting information at the time that the loan is issued. All variables in monetary term are deflated to 2006 RMB.

The set of controls LC_{il} covers loan characteristics, such as the maturity of loan *l* in (log) months, *Maturity*$_{il}$; its (log) size in real terms (deflated to 2006 RMB), *Loansize*$_{il}$; and the difference between its lending rate and the benchmark deposit rate of a corresponding maturity, *Spread*$_{il}$. We also control for monetary policy and regional macro-economic factors (MC_{il} and RC_{il}, respectively) that potentially can influence the pledging of collateral (e.g. Boot et al., 1991; Kiyotaki and Moore, 1997; Jimenez et al., 2006). Monetary policy controls include the reserve requirements ratio, *RRR*$_{il}$ and the 7-day repo rate, *Repo*$_{il}$. These variables are matched to the month when the loan was originated. Regional macro-economic controls are the provincial real GDP growth rate (deflated with national CPI), *Realgdpindex*$_{il}$; provincial non-performing loan ratio, *NPLratio*$_{il}$; and the provincial consumer price index, *CPI*$_{il}$. These variables are matched to one semi-accounting year before the loan was originated. All these data come from the CEIC database.

The last set of controls are fixed effects (FE_{il}) for time (*Time*), bank-type (*Banktype*), province (*Prov*) and industry-type (*Indu*). These fixed effects capture systematic differences related to: business or credit cycles at the national level; bank type specific propensities in requiring collateral; provincial collateral policies; and differences in technology, production, market conditions, and government industry policies across different industries. In total 7 time dummies, 31 provincial dummies, 7 bank type dummies, and 51 industries dummies are introduced.

2.1.2. Informational rent and borrower transparency

This subsection attempts to find evidence that the increasing likelihood of collateral related to relationship lending and market concentration is at least partially due to informational hold-up. To this end, we test if the effects of relationship lending and market concentration on collateral are less pronounced for transparent firms, because information about these firms is more widely distributed among all lenders. Specifically, we test the following specification:

$$\mathrm{P}(\mathrm{Collateral}_{il}) = \mathrm{F}\Big(\beta_0 + \beta_1 \mathrm{Sizeconcen}_{il} + \beta_2 \mathrm{ACR4}_{il} + \beta_3 \mathrm{Sizeconcen}_{il} * \mathrm{Infor}_{il} + \beta_4 \mathrm{ACR4}_{il} * \mathrm{Infor}_{il} + {} + \omega\, \mathrm{Infor}_{il} + \textstyle\sum_{j=1} \sigma_j \mathrm{Relcontrols}_{il} + \rho\, \mathrm{IPO}_{il} + \sum_{j=1} \phi_j \mathrm{FC}_{il} + \sum_{j=1} \theta_j \mathrm{LC}_{il} + \sum_{j=1} \gamma_j \mathrm{MC}_{il} + \sum_{j=1} \delta_j \mathrm{RC}_{il} + \sum_{j=1} \alpha_j \mathrm{FE}_{il}\Big) \quad (2)$$

where an informational transparency measure *Infor*$_{il}$ (higher value representing more transparent) is interacted with the relationship lending and market structure variables (*Sizeconcen*$_{il}$ and *ACR4*$_{il}$, respectively). If $\beta_1 > 0$ and $\beta_3 < 0$, or respectively $\beta_2 > 0$ and $\beta_4 < 0$, it would lend some support to the idea that relationship lending respectively concentrated markets facilitate informational rent extraction, and that rent extraction is relatively more difficult if borrowers are transparent.

We apply two sets of transparency measures (*Infor*$_{il}$): transparency based on firm characteristics, and transparency resulting from stock market information production. The first set of transparency measures includes: listing board (*Listmain*$_{il}$); firm ownership (*FT*$_{il}$); and firm size (*Medianta*$_{il}$). *Listmain*$_{il}$ is a dummy variable that equals one if the firm is listed at the main board of the Shenzhen Stock Exchange, and zero if the firm is listed either at the small and medium-sized firms' board (SME board) or the China Next board (ChiNext board)[12]. Firms listed at the latter two boards are typically smaller or high-tech firms, which should be more informational opaque. Since nearly all banks in China are fully

[12] The listing boards are unknown for loans obtained before the listing. However, both firms and banks should have some idea about which listing board will be the most likely outcome when the firm applies for an IPO, given the characteristics of the firm. The lengthy approval process of the CSRC also suggests that firms need to decide at which board they will list long before the actual listing. As a robustness check, we reproduce the *Listmain* regression using loans issued only after listing. Our results hold for this alternative sample as well. Results are available upon request.

or partly state-owned, it is expected that banks are better informed about state-owned firms than about private firms. Finally, firm size is a standard measure of informational transparency, with smaller firms considered to be more informational opaque. We define a dummy $Medianta_{il}$ that equals one if the firm’s total assets are above the provincial median, and zero otherwise.

The second set of transparency measures is related to stock market information production. Specifically, we postulate that firm transparency increases with the number of financial analysts ($Numalst_{il}$) following the firm, and the percentage of shares held by non-bank institutional investors ($Instishare_{il}$). We further investigate if information spill-over from the stock market generate a boundary transparency level beyond which inside and outside banks are equally informed, and inside banks can no longer extract informational rents. As these information production variables are available only after being listed, we restrict the sample exclusively to post-IPO loans.

However, since these informational transparency proxies are also correlated with the probability of firms’ financial distress or bargaining power, this identification strategy cannot fully differentiate the “hold-up” problem from competing theories. For instance, under the assumption that larger firms are less likely to face financial stress than smaller firms, these firms have less incentive to pledge collateral to relationship lenders in exchange for a possible future rescue, leading to a smaller impact of relationship intensity on collateral incidence on larger firms. The implicit guarantee enjoyed by state owned firms may render collateral irrelevant in exchange for a future rescue from a relationship lender, which can lead to a lower impact of relationship intensity on collateral incidence for these firms. Similarly, as larger firms or state owned firms may have greater bargaining power, market structure could affect their collateral pledging less than that of smaller or private firms. The stock market information production measures could also be positively related to firm size or the financial health of firms. Namely, more analysts are required for larger firms, or non-bank institutional investors target financially healthy firms. These arguments suggest that the coefficients of the interaction terms should be negative, which can be a result independent of the informational rent extraction hypothesis. To better test this hypothesis, in the next sections we use equity IPOs as an informational shock that reveals informational to all banks, and therefore reduces the capacity of inside banks to extract informational rents.

2.1.3. Equity IPOs as strategy to identify informational rent extraction

This subsection formulates the methodology applying equity IPOs to identify informational rent extraction. This strategy hinges on the following observations. Before an IPO, inside banks enjoy superior information obtained from lending relationships, which allows for rent extraction through collateral. After an IPO, the constant release of information and market monitoring prevents any inside bank from obtaining or maintaining an informational monopoly position, therefore alleviating the adverse selection problems facing outside banks. Furthermore, a secondary effect might be at work which reinforces the direct effect of an IPO in reducing information asymmetries among inside and outside banks. Because an IPO will reveal information to all banks, inside banks are less incentivized to acquire additional but costly information to maintain their informational monopoly. This may be caused by a decreasing return on investment in information or an increasing cost of accumulating additional information in markets where all banks are well informed. Banks may also free-ride when costly information production can be conducted and disseminated by the stock market. With less investment in information after an IPO, information asymmetries among banks are reduced further. These arguments suggest that the informational monopolies of inside banks are greatly reduced after IPOs, making rent extraction through collateral less likely.

Similar arguments apply to market structure. As discussed in the Introduction, when borrowers lack a credible channel for disseminating information, such as before an IPO, concentrated markets permit: more efficient information extraction (Marquez, 2002); better reusability of information (Boot and Thakor, 2010; Chan et al., 1986; Berlin and Mester, 1999) and protection of information from spilling over to outside banks; and deters entry of competitors which self-reinforces the information monopolies (Dell’Ariccia et al., 1999; Dell’Ariccia, 2001). After an IPO, information is made public to outside banks through regularly published financial statements, public auditing, financial analysts’ research and movements in stock prices. Hence, the role of market concentration in facilitating information asymmetry among lenders becomes less important, which erodes the possibility of informational rent extraction.

We formulate the following hypotheses:

H.3: If relationship lenders extract informational rents through collateral, this will be more likely for loans originated before the IPO and less likely for those originated after the IPO. If this moderated effect for post-IPO loans is not supported by the empirical results, alternative theories should explain the positive correlation between relationship lending and collateral incidence.

H.4: The positive correlation of market concentration with collateral should be mitigated by the informational shock of an IPO. If this result is not established, the positive impact of market concentration on collateral incidence is attributed to market power.

To test these hypotheses, we introduce interaction terms between the relationship intensity and market structure variables respectively, with IPOs in *Equation (1)*, which yields *Equation (3)*:

$$\mathrm{P}(\mathrm{Collateral}_{il}) = \mathrm{F}(\beta_0 + \beta_1 \mathrm{Sizeconcen}_{il} + \beta_2 \mathrm{ACR4}_{il} + \beta_3 \mathrm{Sizeconcen}_{il} * \mathrm{IPO}_{il} + \beta_4 \mathrm{ACR4}_{il} * \mathrm{IPO}_{il} + \sum_{j=1} \sigma_j \mathrm{Relcontrols}_{il} + \sum_{j=1} \mu_j \mathrm{Relcontrols}_{il} * \mathrm{IPO}_{il} + \rho\, \mathrm{IPO}_{il} + \sum_{j=1} \phi_j \mathrm{FC}_{il} + \sum_{j=1} \theta_j \mathrm{LC}_{il} + \sum_{j=1} \gamma_j \mathrm{MC}_{il} + \sum_{j=1} \delta_j \mathrm{RC}_{il} + \sum_{j=1} \alpha_j \mathrm{FE}_{il}) \quad (3)$$

Informational rent extraction by relationship lenders is identified if $\beta_1 > 0$ and $\beta_3 < 0$. Similarly, market concentration facilitates informational rent extraction if $\beta_2 > 0$ and $\beta_4 < 0$. If $\beta_3 < 0$ or $\beta_4 < 0$ is rejected, the positive coefficients of β_1 and β_2 should be explained by other theories as discussed in Introduction. We include the interaction term *Relcontrols*$_{il}$ * *IPO*$_{il}$ to control for the possible heterogeneous impact of other relationship characteristics on collateral incidence before and after an IPO.

Two important caveats must be kept in mind. First, as discussed in the Introduction, the moderated effect of relationship lending on collateral could be explained by theories other than informational rent extraction. We discuss and test these alternative explanations in Section 4. A second caveat is related to the endogeneity assumption of IPOs and relationship lending. In practice both variables could be endogenous due to omitted variables. We address these issues using recursive bivariate probit models in Section 5. We discuss some further robustness tests in Section 6.

2.1.4. Informational rent extraction and firm risk

Rajan (1992) suggests that inside banks can charge informational rents more easily from riskier borrowers than from safer ones, because outside banks will be less inclined to lend once the borrower is revealed as risky. This view suggests that when information asymmetry between inside and outside banks is alleviated, rent extraction will decline for safer firms but not for risky ones. We test to see if this prediction applies to collateral as well (see Hale and Santos (2009) for similar tests on lending rates).

We propose a novel measure of firm risk: whether the first IPO application of a firm was rejected by the CSRC ($Multiapp_{il}$). A firm can be rejected for an IPO by the CSRC for many reasons, such as cash-flow problems, uncertain or weak profitability perspectives, unclear corporate governance structures or suspicious earnings, all of which suggest potential risk factors that do not meet CSRC listing requirements. In a way, this measure is similar to a credit rating (see an application in Hale and Santos, 2009), but now the firm is rated by a government body instead of private sector rating companies. To test this hypothesis, we expand the baseline *Equation (3)* with three-way interaction terms between informational rent variables ($Sizeconcen_{il}$ and $ACR4_{il}$), IPO_{il}, and firm risk proxy $Multiapp_{il}$.

2.2. Data

We manually collect *loan-level* data from listed firms' financial reports, published by Wind Finance Co., Ltd. Hence, our analysis departs importantly from most studies on Chinese loan markets, which either use yearly aggregate *firm-level* data from the China Securities Markets and Accounting Research Database (CSMAR) (e.g. Firth et al., 2012; Chen et al., 2013) or rely on loan-level datasets provided by *few* state-owned banks (Chang et al., 2014; Qian et al., 2015).

Our dataset consists of 10,654 loans made to 676 firms listed at the Shenzhen Stock Exchange (SZSE) between 2007 and 2013.[13][14] The size of the sample is reduced by some recording errors, incomplete loan contract information and questionable financial data. In particular, loans issued at rates below the lending rate floor (i.e. below 90% of the baseline lending rate) are removed, because these loans are likely to have been issued at non-commercial terms. We further remove loans to financial institutions and loans made in foreign currencies. This reduces our database to 9,288 loans provided to 649 listed non-financial firms. Our database provides information on multiple borrowings by each firm (on average, each firm has 20 loans in our sample) and from multiple banks (on average 4 banks per firm), including almost all types of Chinese banks.

Summary statistics for all variables are provided in Table I. 66% of the loans in our database are collateralized, which is comparable to figures recorded for other emerging market economies, such as 53% for Mexico (La Porta et al., 2003) and 72% for Thailand (Menkhoff et al., 2006). Our main relationship variable $Sizeconcen_{il}$ has an average value of 0.33, suggesting that on average around one third of loans are obtained from a firm's current lender. The concentration ratio $ACR4_{il}$, which is our proxy for market structure, has an average of 0.55, indicating that the four largest banks in each province on average hold 55% of total provincial banking assets.

The summary statistics for IPO_{il} show that 83% of the loans in our sample were issued after an IPO. Among the 649 firms in our sample, 111 firms reported at least one loan before their IPO and at least

[13] We concentrate on listed firms from Shenzhen Stock Exchange because firms listing at this stock exchange market are more diverse in terms of size and industry when compared with those listed at the Shanghai Stock Exchange. Our sample starts from 2007 because listed firms were required to comprehensively report their loan records from 2007.

[14] Unfortunately, listed firms do not report whether their loans are syndicated loans or not. This shortcoming is unlikely to affect our analysis as syndicated loans are rare in China. Pessarossi et al. (2012) investigate syndicated loans obtained by Chinese listed firms for the period 1999-2009. Only a very small sample of 92 loans is registered for this period. The syndicated loan market in China amounted to less than 30 billion dollars in 2009 (Dealscan), a very small number compared to the total amount of loans outstanding.

one after; in total these firms account for 2,181 loans, representing 23% of all loans. The remaining firms only had loans either before their IPO (142 firms with 660 loans) or after (396 firms with 6,447 loans). Furthermore, our sample consists of relatively old (on average 13 years) and large firms (average total assets of RMB 2,139.5 million). Regarding firm ownership (FT_{il}), firms with state majority ownership represent 33% of all firms in our sample and account for 40% of all loans.

Regarding the controls for loan characteristics, the average maturity of the loans in our sample ($Maturity_{il}$) is around two years (25.9 months), while the average size ($Loansize_{il}$) in real terms is RMB 62.6 million. The average spread between loan lending rates and corresponding deposit rates ($Spread_{il}$) is 2.85%.

Of the other controls, we provide further detail only on the variable that we use to investigate rent extraction and firm risk, i.e. $Multiapp_i$, which measures whether the firm is rejected in its first IPO application. 40 firms, or around 7% of all firms, were rejected for an IPO when they applied for the first time (but were eventually listed, after multiple applications). The definition and summary statistics for each instrumental variable and additional variables are discussed in their respective sections, but are all reported in Table I, panel F, G.

3. Main results

3.1. Univariate tests

This subsection investigates whether the mean values of the key variables differ across relationship intensity, market structure and for pre- and post-IPOs loans. Results are reported in Table II.

Relationship loans, defined as the ones with $Sizeconcen_{il}$ above the sample median, on average enjoy better loan terms such as longer maturity and lower lending spreads. At the same time, these loans are smaller; however collateral requirements do not differ significantly between relationship and non-relationship loans.

Collateral requirements are significantly more severe in concentrated markets, where concentrated markets are defined as the ones with $ACR4_{il}$ above the sample median. Loan maturity does not differ across markets, while loan size and the average lending spread are significantly larger in less concentrated markets. Lastly, loan contract terms such as collateral (-), maturity (+) and loan size (+) change significantly after listing (in brackets change after IPO compared to before), while the average lending spread does not differ for loans issued before and after IPOs.

Firm characteristics do not depict a clear pattern between groups. For instance, firms that borrow from relationship lenders are on average more liquid, less leveraged and have higher tangibility ratios. However, they are also younger and smaller than firms borrowing from non-relationship banks. Firms that borrow in concentrated markets are on average less liquid, smaller, younger and more leveraged, and have higher tangibility ratios. Lastly, firms that borrow after an IPO are less liquid and less profitable, but the leverage ratio of borrowing firms does not differ before and after the IPO.

3.2. Multivariate tests

3.2.1. Do relationship lending and market structure determine collateral incidence?

In this section, we first test the impact of relationship lending and market structure on collateral incidence in a cross-sectional setting by estimating *Equation (1)* in Section 2.1.1. The results are reported in Panel A of Table III. Marginal effects (M.E.) are calculated based on the results in Column (1). To account for the possibility that some loan contract terms such as *Maturity* and *Spread* are endogenous, we follow Berger and Udell (1995) and estimate the model with and without these terms (Columns (1) and (2), respectively). We conduct additional robustness tests for endogeneity issues of loan contract terms in Section 6.2.

Our results show that relationship intensity is positively related to the incidence of collateral and is highly significant. The marginal effects show that a one standard deviation increase in *Sizeconcen* from its sample mean increases the probability of collateralization by 1.4%. This result does not support the "information accumulation" view that relationship lending and collateral are substitutes in mitigating borrower risks (e.g. Berger and Udell, 1995). In contrast, our finding is in line with the other hypotheses discussed in Introduction (e.g. "hold-up" problem (Sharp, 1990; Rajan, 1992), "soft budget constraint" (Dewatripont and Maskin, 1995; Boot, 2000), "bank seniority" (Longhofer and Santos, 2000) and "cost minimization incentive" (Menkhoff et al., 2006)). Results similar to ours have been reported in e.g. Elsas and Krahnen (2000), and Ono and Uesugi (2009).

Market structure, measured as the concentration ratio *ACR4*, is positive and highly significant at the 1% level across all specifications. A one standard deviation increase in this ratio increases the likelihood of collateral incidence by 4.45%. This result confirms Hypothesis *H.2* (Section 2.1.1) that concentrated markets are associated with a higher likelihood of collateralization. Our finding is in line with Hainz et al. (2013), but contrasts with Jimenez et al. (2006). As discussed, both the "informational rent extraction" and "market power" hypotheses can explain this positive coefficient.

The coefficient of *Numlender* is significant and positive as well. A one standard deviation increase in the number of lenders of the firm from its mean increases the incidence of collateral by 2.13%.[15] Other relationship control variables such as *First* and *Switch* are not statistically significant; we shall discuss these results in more detail later on.

Loans obtained after an IPO are significantly less likely to be collateralized (marginal effect is -10.39%). This result lends some support to the notion that IPOs are beneficial to firms with respect to the non-price terms of lending. This adds to the empirical findings in Santos and Winton (2008), Hale and Santos (2009) and Schenone (2010) that loan terms improve after bond or equity IPOs, with these studies presenting evidence of a decline in lending rates.

[15] This result is in line with Chakraborty and Hu (2006) and Jimenez et al. (2006), but in contrast to Menkhoff et al. (2006).

Before moving forward, we discuss briefly other determinants of collateral, which has merit in itself, as the existing literature on Chinese lending markets has investigated this issue only using firm-year data (e.g. Firth et al., 2012; Chen et al., 2013). As expected, the coefficients of *Age* and *Size* are negative and significant, indicating that older and larger firms are less likely to pledge collateral, possibly because these firms are less prone to moral hazard problems. Firms that are more profitable, more liquid, have a higher tangible assets ratio and are less leveraged are less likely to pledge collateral. Similar to Berger and Udell (1990), we find that *Loanconcen* is significantly positive at the 1% level across all specifications.[16] Among all factors, the most important determinant of collateral is firm ownership. Private firms in China have on average a 16.7% higher probability of pledging collateral than state-owned firms, presumably because the latter enjoys the implicit guarantee from the State. This results adds to the previous empirical studies that private firms in China have been financially discriminated in a state-dominant banking system (Cull and Xu, 2003; Allen et al., 2005).

Other loan contract terms affect the incidence of collateral as well. Loans with a longer maturity are more likely to be collateralized. A one standard deviation increase in loan maturity from its sample mean increases the incidence of collateral by 3.39%. This result is in line with the theoretical prediction that banks use shorter loan maturities to solve adverse selection or moral hazard problems (e.g. Berlin and Mester, 1992; Flannery, 1986; Barclay et al., 1995; Degryse and Van Cayseele, 2000). Larger loans (*Loansize*) are less likely to be collateralized. A one standard deviation increase of loan size reduces the incidence of collateral by 3.37%.[17] Finally, loans with a higher interest rate spread (*Spread*) are more likely to be collateralized (marginal effect of 1%) giving some support to the notion that collateral is associated with risky loans. Nevertheless, the results for contract terms on collateral should be treated with caution, as these variables are potentially endogenous. Excluding potentially endogenous loan contract terms such as *Maturity* and *Spread* does not alter our results for other determinants, as shown in Column (2).

In contrast, the monetary policy stance has a limited impact on the incidence of collateral, with only the

[16] See for instance Boot et al. (1991), Dennis et al. (2000) and Bharath et al. (2011) for similar results.
[17] This result is consistent with Leeth and Scott (1989), Jimenez and Saurina (2004) and Menkhoff et al. (2006), but in contrast to the findings of Boot et al. (1991).

7-day Repo rate being positively related to collateral at the 10% significance level.[18] Regional macroeconomic variables (*CPI*, *NPLratio* and *Realgdpindex*) generally do not affect collateral decisions. It is likely that the impact of business cycles is captured by time fixed effects, which show that collateral incidence is significantly lower during the 2010-2013 period relative to 2007 (base year). Lastly, loans from foreign banks are significantly more likely to be collateralized, while loans from trust and finance companies and other financial institutions (mainly credit companies) are significantly less collateralized, compared to the benchmark state-owned banks. As a further robustness check, we include regional legal and institutional variables.[19] Our results do not materially change when these additional controls are added.

3.2.2. Does rent extraction vary with firm information transparency?

We test in this section if informational rent extraction is less pronounced for transparent firms. To this end, we estimate *Equation (2)* in Section 2.1.2 using various informational transparency proxies. Results are reported in Table III, Panel B and C, where Panel B uses firm characteristics as transparency measures, and Panel C employs stock market information production as transparency measures.

Firms that are not listed at the main board, privately owned or smaller, are more likely to pledge collateral when relationship intensity increases, as suggested by the significantly positive coefficients of $Sizeconcen_{il}$ in all specifications of Panel B. For transparent firms, the impact of $Sizeconcen_{il}$ on collateral vanishes, as the null-hypothesis H_0: $Sizeconcen_{il}+Infor_{il}*Sizeconcen_{il} = 0$ is not rejected for all

[18] Jimenez et al. (2006) find that collateral incidence is lower during episodes of monetary tightening. They resort to credit rationing to explain their results, since during tightening periods banks prefer high-quality borrowers (hence less collateral). Bernanke and Gertler (1995) suggest that higher interest rates raise a firm's default probability, resulting in a higher likelihood of collateral incidence during monetary policy tightening cycles. Our insignificant result could be due to the combined effect of competing theories, which we leave to future research.

[19] Empirical studies have identified that banks are better able to control for credit risk if legal frameworks allow lenders to seize collateralized assets in times of default (Qian and Strahan, 2007). We employ the indices of legal infrastructure developed by Fan and Wang (2011). These indices have been widely applied for China (e.g. Firth et al., 2009; Li et al., 2009), with Li et al. (2009) providing a detailed description. As data for these indices end in 2009 (while our sample ends in 2013), we interpolate the missing values by assuming that the indices grow at the average growth rate of 2006-2009. Our results show that collateral is more likely to be pledged in provinces with better legal infrastructure, a result that is similar to Qian and Strahan (2007). These authors suggest that a better protection of credit rights increases the incidence of collateral for firms with more tangible assets. The results that we present in the rest of the paper are not sensitive to the inclusion of these legal and institutional variables. Results are available upon request.

three informational transparency measures. As for the impact of market structure on collateral, a similar pattern prevails. The concentration ratio $ACR4_{il}$ is statistically positive in all specifications, and its interaction term with information transparency measures is significantly negative for all three cases. Unlike for relationship lending, the null hypothesis that market structure has no impact on collateral for transparent firm (e.g. firms listed at the main board or state-owned firms), i.e. $ACR4_{il}+Infor_{il}*ACR4_{il}=0$, is rejected. Both results suggest the inside banks' ability to charge rent decreases with firms' information transparency.

Next we employ stock market information production variables ($Numalst_{il}$ and $Instishare_{il}$) as proxies of firm transparency. Results are reported in Panel C, Columns (6) and (7). All interaction terms are significantly negative, indicating a moderated effect on rent extraction when more information is produced by stock market, a result similar to Panel B. Moreover, the magnitude of the coefficients further suggests a boundary effect of information production on rent extraction. In other words, rent extraction becomes infeasible when sufficient information is produced by stock market. Specifically, in Column (6), when a borrower is followed by more than 11 analysts (65^{th} percentile), the positive impact of *Sizeconcen* vanishes. Similarly, higher market concentration does not increase collateral incidence for borrowers followed by more than 22 analysts (88^{th} percentile). Column (7) reports similar results where *Instishare* serves as a measure of information production[20]. The thresholds for relationship lending and market concentration to charge rents are 20% (55^{th} percentile) and 70% (96^{th} percentile) of shares held by non-bank institutional investor, respectively. For firms with institutional shareholdings above these values, rent extraction becomes infeasible. The results in this subsection are in line with the informational rent hypothesis. However, as discussed in the Introduction and Section 2.1.2, alternative theories can also support these finding as information transparency measures are often correlated with firm quality or likelihood of financial stress. We proceed in the next subsection using IPO as an identification strategy.

[20] Arguably, institutional investors not only bring on board more information disclosure, but also active monitoring and better alignment of management incentives, such as reducing tunneling behavior (e.g. Lin et al., 2011). We control for these effects by incorporating corporate governance variables that directly affect firms' tunneling incentives: the "control and cash flow rights wedge" and cash-flow rights. Our results remain intact, and they are available upon request.

3.2.3. Do equity IPOs reduce informational rents?

In this subsection, we provide a direct test of informational rent extraction, i.e. we compare the impact of $Sizeconcen_{il}$ and $ACR4_{il}$ on collateral incidence for pre-IPO and post-IPO loans where information asymmetry among lenders is significantly lower for the latter group than the former. Estimations are based on *Equation (3)*.

Results are reported in Table IV. Column (1) includes only the interaction term $Sizeconcen_{il}$* IPO_{il}; Column (2) includes only the interaction term $ACR4_{il}$ * IPO_{il}; Column (3) includes both, while Column (4) re-estimates Column (3) excluding possible endogenous loan contract terms (*Maturity* and *Spread*). The results show that $Sizeconcen_{il}$ is significantly positive across all models. The coefficient of the interaction term $Sizeconcen_{il}$*IPO_{il} is negative and significant for the broader specification (Column (3)), while it is marginally insignificant (p-value 0.102) in Column (1). The coefficient of $ACR4_{il}$ is significantly positive while the interaction term with IPO_{il} is significantly negative across all specifications. As the results of these three specifications are quantitatively similar, we provide a detailed explanation of the results presented in Column (3) only, which is our baseline model.

The likelihood of pledging collateral is increasing with relationship intensity for pre-IPO loans (coefficient 0.596***), while for post-IPO loans this positive impact is greatly moderated (coefficient 0.124*, and H_0: $Sizeconcen_{il}+Sizeconcen_{il}*IPO_{il}=0$ is rejected at the 10% level). In terms of marginal effects, a one standard deviation increase in $Sizeconcen_{il}$ increases the probability of pledging collateral by 4.78% for pre-IPO loans, compared to 1.17% for post-IPO loans. This pattern is consistent with Hypothesis *H.3* (Section 2.1.3) that a reduction in informational asymmetry among lenders makes it harder to establish "hold-ups" through relationship lending, therefore lowering the likelihood of rent extraction through collateral.

A similar pattern is observed for market structure. The pre-IPO coefficient of the concentration ratio $ACR4_{il}$ is 5.94***, indicating that pre-IPO loans obtained in concentrated markets are significantly more likely to be collateralized. The post-IPO impact of $ACR4_{il}$ is moderated, but remains statistically positive (coefficient 2.43***, H_0: $ACR4_{il}+ACR4_{il}*IPO_{il}=0$ rejected at 1%). Alternatively, looking at the marginal effects, a one standard deviation increase in the concentration ratio increases the probability of collateral incidence by 8.51% for pre-IPO loans, while for post-IPO loans this effect is reduced to 4.15%. Hence, the contribution of concentrated markets in facilitating the extraction of information, or preventing its spill-over to competitors, is greatly eroded, since more information about borrowing firms has been disseminated due to the IPO. This more equal distribution of information further reduces *de novo* banks' adverse selection problems and lowers barriers to entry, which is another reason why informational rent extraction is more difficult for post-IPO loans. This result confirms Hypothesis *H.4* (Section 2.1.3).

We find the positive impact of market concentration on collateral is both statistically and economically significant even for post-IPO loans. The presence of a certain degree of information asymmetry among lenders even post-IPO could explain this results. This result could also lend some support to the view that information asymmetries are not the only channel leading to higher collateral incidence in concentrated markets. The "market power channel", discussed in the Introduction, suggests that monopolistic or oligopolistic banks can extract rents by using their market power, increasing collateral requirements even in an environment where all lenders are equally informed. This channel could be particularly important for banking markets characterized by geographic restrictions in branch expansion or restrictions in business scope. Furthermore, given that our sample is composed of large listed firms whose funding needs might not be served by smaller banks, large banks can enjoy their market power further, even when borrower information is equally distributed among inside and outside lenders.

It is likely that firms gain bargaining power vis-à-vis lenders after their IPO, for example because the listing improves their access to capital markets or increase their attractiveness as clients for other lenders. This reduces the positive impact of relationship lending or bank market structure on collateral incidence. Nevertheless, at least part of the bargaining power gain is due to the higher visibility of post-IPO information dissemination, which makes it extremely hard to differentiate information and bargaining power effects[21]. We control for possible shifts in a borrowing firms' bargaining power by introducing an interaction term $Numlender_{il}*IPO_{il}$. Firms that can borrow from different lenders might be expected to benefit from higher intra-bank competition and therefore have more bargaining power vis-à-vis their current lender(s) (Yasuda, 2007). In our univariate tests, we found that an average firm borrows from two banks before an IPO, while this number increases to four after the IPO, suggesting increasing bargaining power. However, the coefficients on $Numlender_{il}$ and $Numlender_{il}*IPO_{il}$ are both insignificant.

Next, we briefly discuss the other control variables. $First_{il}$ is significantly positive for pre-IPO loans, indicating that borrowing for the first time from a certain lender before an IPO is associated with a higher likelihood of collateral pledging. For post-IPO loans, collateral incidence is not affected by whether the loan is the first one from a certain lender or not (H_0: $First_{il}+First_{il}*IPO_{il}=0$ cannot be rejected). This pattern is fairly persistent throughout all our regressions, which further supports the role of IPOs in disseminating information. Before an IPO, the first loan is associated with higher collateral incidence due to limited knowledge of the borrower. However, this significant relationship disappears after the IPO, given that the IPO process and post-IPO information disclosure increases the transparency of the borrowing firm to all potential lenders. Switching lenders ($Switch_{il}$), however, does not affect collateral incidence before or after the IPO. The coefficients on other control variables are similar to those reported in Table III, which are available upon request.

To conclude, using IPOs as an informational shock, the results in this section provide evidence of informational rent extraction, whether the informational advantage is driven by relationship lending or concentrated markets. As discussed in the Introduction, the results of this section are subject to caveats related to alternative explanations and endogeneity issues of key variables, which we examine in Section 4 and 5.

[21] Pagano et al., (1998) suggest that it is impossible to distinguish information and bargaining power effects of IPO. Saunders and Steffen (2011) investigate the bargaining power effect of IPO through information effect.

3.2.4. Do informational rents vary with firm risk?

Finally, we test whether following an IPO, informational rents reduce for safe firms, but not, or to a lesser extent, for risky firms. We introduce a three-way interaction term between our informational rent variables ($Sizeconcen_{il}$ or $ACR4_{il}$), IPO_{il} and the firm risk proxy $Multiapp_{il}$. Results are reported in Table V.

In the first column, we examine the main effect of $Multiapp_{il}$. A firm with multiple applications is 7% more likely to pledge collateral than first-time approved firms, which is consistent with our belief that being rejected for IPO is associated with higher firm risk. Three-way interaction terms are introduced in Column (2). Our results show that the marginal effects of the informational rents variables ($Sizeconcen_{il}$ and $ACR4_{il}$) on collateral are all *positive* both before and after IPOs. However, whether these marginal effects are moderated after an IPO depends on the riskiness of firms. To see this, we calculate the *change* in the marginal effects of the informational rent variables after and before IPO, for safe ($Multiapp_{il}$=0) and risky firms ($Multiapp_{il}$=1). For safe firms, the marginal effects of $Sizeconcen_{il}$ on collateral drops by 4% after the IPO, while for risky firms, it increases by 3.2%. Similar results are found for market structure. The marginal effect of $ACR4_{il}$ drops by 6% for safe firms after the IPO, but for risky firms it increases by 5.5%.

These results show that the ability of inside banks to charge informational rents after an IPO falls for safer firms, but increases for risky ones. This is because once the borrower is identified as safe, outside banks bid aggressively for lending business, reducing the inside bank's monopoly power. In contrast, outside banks will be less interested in lending to risky firms when the latter's poor creditworthiness is revealed, strengthening the ability of inside banks to extract rents. We test the robustness of these results by removing loan contract terms (Column (3)) and monetary policy and regional macroeconomic variables (Column (4)). In all cases, our results remain the same.

4. Alternative explanations

As noted earlier, the moderated effect of relationship lending on collateral incidence for post-IPO loans could be explained by alternative theories, which we discuss in this section.[22] One possible alternative is that credit quality is significantly higher for listed firms compared to unlisted ones. In other words, it is higher credit quality instead of lower information asymmetry that explains this moderated effect. The second possible explanation is related to banks' selection of distributing loans. The final alternative explanation that we explore is that relationship banks reduce their collateral requirements in exchange for corporate bond underwriting business. We do not find supporting evidence for the first two alternative explanations and the last alternative explanation cannot dismiss the informational rent extraction hypothesis.

4.1. Higher credit quality of listed firms

Boot (2000) and Longhofer and Santos (2000) (see Introduction) predict a weaker positive correlation between relationship lending and collateral incidence for financially sound firms relative to distressed firms. If listed firms are financially healthier than unlisted ones, it would reduce the need to post collateral from the relationship lender's perspective, as the risk of financial distress and the likelihood of engaging in a future rescue is lowered. However, various studies have shown that the operating performance of listed Chinese firms drops markedly after an IPO. For example, Allen et al. (2014) compare the operating performance of listed and non-listed firms in China for the years around an IPO and find that the average return on assets of listed firms drops significantly from 0.12 to 0.07 within a [-3, 3] years window. This sudden drop is not observed for the unlisted firms over the same time horizon. These authors attribute the deterioration in performance to the extremely strict listing requirements of the CSRC,[23] which induce firms to improve earnings in the years prior to an IPO,

[22] We can discard one alternative explanation of the positive correlation between collateral incidence and relationship lending intensity that we find. This is the "cost minimization incentive" view (Menkhoff et al., 2006), which we discussed in the Introduction. This interpretation is not able to explain our results, as this incentive is unlikely to change depending on whether the borrower is listed or unlisted. Hence, the observed significant and negative coefficient of the interaction term $Sizeconcen_{il}*IPO_{il}$ is not supported by this theory.

[23] To be approved for listing, firms need to report positive earnings in the three consecutive years prior to the IPO or have accumulated at least 30 million in net income. In addition, firms are required to have accumulated net cash flows of more than 50 billion or revenues in excess of 300 million in the three years prior to the IPO.

adjusting operations to generate short-term profits at the possible cost of long-term growth. Similar evidence is also found in our sample where the average return on assets for pre-IPO firms is around 10% higher than post-IPO firms (e.g. from 15% prior to the IPO to 5% after, see Table II).

To further address selection bias in listing status caused by observables, we employ a propensity score matching method. The propensity score of loans being borrowed by listed firms is estimated based on a set of variables determining an IPO. Using nearest neighbor matching, loans borrowed by listed firms are then matched to the ones borrowed by unlisted firms. We drop loans that are outside of the common support to minimize the potential bias introduced by these loans. This process generates a matched sample of loans that are “identical” in every aspect, except for the borrower’s listing status. We re-estimate the baseline model in Table IV, Column (3) on this matched sample. Our results do not materially change (available upon request) and so we conclude that higher observed credit quality of listed firms is unlikely to drive our results.

Obviously, the credit quality of listed and unlisted firms may also differ in an immeasurable way. We conduct further analysis in Section 5 to account for these unobserved risk factors.

4.2. Selection effect

Suppose the relationship dependent listed firms that obtained loans are on average safer than relationship dependent unlisted firms, while the relationship non-dependent listed firms that obtained loans are on average riskier than relationship non-dependent unlisted firms. This selection effect could explain the moderated effect of relationship lending on collateral for post-IPO loans. To address this concern, we perform difference-in-difference tests for observed risk proxies broken down by whether a firm is relationship dependent and whether the loan is borrowed after an IPO. In a fashion similar to Presbitero and Zazzaro (2010), a relationship dependency dummy is defined as equal to 1 if *Sizeconcen* is above or equal to the sample median (0.20). We construct difference-in-differences tests for the key financial risk proxies (*ROA*, *Leverage*, *Tangibility*, *Liquidity*, *Size*, *Maturity*, *Spread* and

Loansize). For each of these variables, we compute the mean values broken down by relationship dependency and listing status. We then calculate for each firm type (relationship dependent or not) the mean difference between listed and unlisted samples, and investigate whether the difference between these two differences is significant. This procedure is equivalent to estimating a linear regression for each of the firm risk proxies on IPO_{il}, relationship dependency dummy, and the interaction terms between these two variables. The coefficient on the interaction term and its statistical significance indicates whether relationship dependent and non-dependent firms differ significantly depending on their listing status. Results are reported Internet Appendix Table IA.I. In all these difference-in-differences tests, the interaction terms are statistically insignificant except for *Liquidity*. Hence, the selection effect we postulated is unlikely to be a key driver of our results.

Finally, we conduct matched sample analysis within pre- and post-IPO samples and compare the impact of relationship lending on collateral pledging across samples. This way we remove the possibility that firm-risk dynamics around IPOs could be driving our results. If relationship banks charge informational rents and if IPOs reduce information asymmetry among lenders, the average treatment effect of relationship lending should be positive for pre-IPO loans and be moderated or insignificant for post-IPO loans. We find that relationship dependent firms are on average 10% to 12% more likely to pledge collateral relative to matched non-dependent firms for pre-IPO loans, while the difference between these two groups vanishes for post-IPO loans. Technical details, estimation results and sensitivity tests (including balancing property of covariates and sensitivity to unobservables) are reported in the Internet Appendix, Section A and Tables IA.II-III.

4.3. Corporate bond underwriting and concurrent lending

Banks may exchange better loan conditions for corporate bond underwriting business.[24] As most firms have a bond IPO after an equity IPO, and many firms choose their relationship banks as underwriters, the moderated effect of relationship lending for post-IPO loans could be the result of exchanging better

[24] For instance, Yasuda (2007) documents that firms in Japan obtain a fee discount when employing relationship banks as corporate bond underwriters.

loan conditions for bond underwriting fees, instead of an informational equalization effect. Our sample includes 1,287 loans that were originated after the firms' bond IPO, which is a sizeable sample. To address this issue, we construct various samples that only incorporate loans granted before a firms' bond IPOs. If our results are driven by concurrent lending and corporate bond underwriting, once we exclude loans borrowed after the bond IPO, the significant results for the interaction term $Sizeconcen_{il}*IPO_{il}$ should vanish. We find that this is not the case. Results are reported in the Internet Appendix, Table IA.IV.

5. Endogeneity of IPO and relationship lending

In previous sections, we have treated the IPO or relationship lending variables as exogenous. As discussed in the Introduction, they could be endogenous due to unobserved risk factors. We apply recursive bivariate probit models to address the potential endogeneity issue of IPOs in Section 5.1, and that of relationship lending in Section 5.2. Our results are robust after controlling for these endogeneity issues.

5.1. Endogeneity of IPO

The fact that all of the firms in our sample have eventually completed their IPOs alleviates the endogeneity concern of IPO to some extent. However selection bias could still be present due to unobserved factors. As discussed in the Introduction, the exact timing of an IPO is to a large extent unpredictable for firms, but it is possible that there are uncontrolled factors that could affect both the timing of an IPO and collateral. For instance, firms' political connections (unobserved to econometricians) can speed up the listing process and at the same time lower collateral requirement as banks may consider politically connected firms less risky. This omitted variable problem makes the IPO variable and its interaction terms with other covariates in *Equation (3)* correlated with the error term in the equations, leading to biased estimates. To address this issue, we follow Wooldridge (2010, Chapter 15.7.3) and implement a recursive bivariate probit model with instrumental variables[25]. The model is estimated with Maximum Likelihood Estimation (MLE). Besides consistency and efficiency of the MLE, a crucial benefit of this approach is that we can easily estimate the interactions of binary endogenous variable with exogenous variables in the structural equation (Wooldridge 2010, page 596)[26]. One simply needs to specify that the only source of endogeneity comes from the binary treatment variable, treating the interaction terms in the structural equation as if they were exogenous. Specifically, we estimate the following model:

$$Collateral = 1[Z_1\alpha_1 + IPOX_1\beta_1 + \varepsilon_1] > 0$$

$$IPO = 1[Z_2\gamma + \varepsilon_2] > 0 \tag{4}$$

where Z_1 is a vector of collateral determinants and X_1 contains unity and variables that are allowed to be interacted with IPO. This *Collateral Equation* is the same as *Equation (3)*. In the *IPO Equation*, Z_2 contains all variables in Z_1 and at least one additional instrumental variable, i.e. it contains some exogenous variable that affects listing status, but does not explain collateral except through firm's listing status[27]. The error terms are assumed to be bivariate normal distributed with correlation ρ, i.e. $\varepsilon_1, \varepsilon_2 \sim \emptyset(0, 0, 1, 1, \rho)$.

We derive our instrumental variables from CSRC IPO suspensions. By the end of 2013, the CSRC has unexpectedly suspended the IPO reviewing and approval process on eight occasions[28]. These suspensions were unforeseeable by banks or borrowers, and therefore can serve as exogenous shocks. During these suspension periods, no new IPOs were approved, while firms that had already started their IPO applications were forced to stop it. These suspensions affect listing status for at least

[25] Since IPO is a binary variable, the traditional two-stage least squares models will produce inconsistent estimators (Green, 2008).

[26] The existence of endogenous interaction terms in the structural equation causes no problem for MLE estimation of the bivariate probit model because the density function of the outcome variable is conditional on all exogenous variables and endogenous binary variable (or function of endogenous binary variable), therefore the conditional density function is the same whether or not endogenous binary variable (or function of endogenous binary variable) enters the structural equation.

[27] Wilde (2000) shows that exclusion restrictions are not generally needed in a multi-equation probit system and that identification is achieved if varying exogenous regressors appear in both equations of the bivarate probit model. Wooldridge (2010) however recommends not relying on nonlinearities solely to identify parameters in bivariate probit models.

[28] By the end of 2013, the CSRC IPO suspension periods are: 1) 1994/7/21-1994/12/7; 2) 1995/1/19-1995/6/9; 3) 1995/7/5-1996/1/3; 4) 2001/7/31-2001/11/2; 5) 2004/8/26-2005/1/23; 6) 2005/5/25-2006/6/2; 7) 2008/9/16-2009/7/10; 8) 2012/11/16-2013/12/31.

two reasons: firstly, listings will be delayed as the amount of reviewing work for the CSRC to complete piles up; and, secondly, some applicants need to prepare their application documents again as previous documents expire after the IPO suspension; this is costly and sometimes infeasible for firms that have exhausted their resources to boost up their accounting performance.

Naturally, it is unrealistic to assume that IPO applications are affected by all past CSRC suspensions. Only the ones that occur during firms' preparation period should affect their IPOs. The actual dates when firm started their preparation process are unknown, but the preparation and completion of IPO usually takes at least 1 to 3 years. We take the middle value of 2 years prior to actual listing dates as our cut-off point, which ensures that most of the applicants have started their preparation process[29]. Our first instrument is a dummy variable, *Affected_Firms*, which equals 1 if firms experienced at least one CSRC IPO suspension during the two-year window prior to their actual listings. 442 (68% of all firms) firms satisfy this condition, and in total these firms borrowed 6351 loans (68% of all loans) throughout our sample period. We further calculate the number of IPO suspension days within this 2-year window as our second instrument, denoted it as *dd_lag2*. The average suspension days for *Affected_Firms* are 258 days. For unaffected firms, the number of suspension days is zero. To address skewness, we use *log(1+dd_lag2)* in the estimation.

The results of the recursive bivariate probit model are reported in Table VI. For comparison purpose, Column (1) reproduces the baseline mode of Table IV, Column (3). Column (2) and (3) estimate the recursive bivariate probit model using *Affected_Firms* and *log(1+dd_lag2)* as instruments, respectively. For brevity we report the key results only. Looking at the instrumental variables in the *IPO Equation*, we find the coefficients of *Affected_Firms* and *log(1+dd_lag2)* and are negative and statistically significant at the 1% level, consistent with our projection that IPO suspensions affect listing status. More importantly, after controlling for the endogeneity of IPO, the coefficients of the key variables in the structural equation (*Collateral Equation*) are very similar to the single Probit estimation results in Column (1). This result should not come as surprise since the MLE estimates of the correlation coefficient ρ are statistically insignificant in both Column (2) and (3), indicating that the exogeneity

[29] Defining a 3-year window does not materially change our results. Results are available upon request.

assumption of IPO cannot be rejected, which further justifies our estimations in previous sections using a single equation Probit model.

The validity of instruments obviously hinges on the assumption that CSRC IPO suspensions do not influence collateral incidence directly. Unfortunately this assumption is not testable. An informal test of exclusion restrictions can be derived by including the instrumental variables in the structural equation and testing to see if their coefficients are statistically significant. The coefficients of *log(1+dd_lag2)* and *Affected_Firms* are -0.009 (p-value 0.22) and -0.03 (p-value 0.53), both of which are statistically insignificant. Another caveat is that banks may consider CSRC IPO suspensions as negative shocks to affected firms. Consequently, banks may raise the collateral requirement should these firms borrow during the suspension periods. This could relate the CSRC IPO suspensions to the incidence of collateral, therefore violating the exclusion restriction. To test this, we define a dummy variable *Affected_Loans,* which equals 1 if loans are borrowed by *Affected_Firms* during suspension periods. 1410 loans (15% of our sample of loans) satisfy this condition. We re-estimate the baseline model (Table IV, Column (3)) including the *Affected_Loans* dummy. If banks consider CSRC IPO suspensions as negative shocks to these firms, *Affected_Loans* should be significantly positive. The coefficient of *Affected_Loans* is positive (0.04, with p-value 0.48), but statistically insignificant[30].

In summary, these tests are consistent with our view that collateral incidence is independent of CSRC IPO suspensions, and *log(1+dd_lag2)* and *Affected_Firms* are valid instruments. Furthermore, our main results hold after controlling for the endogeneity of IPOs.

5.2. Endogeneity of relationship lending

Relationship lending could also be endogenous due to omitted variables affecting both relationship formation and collateral[31]. For instance, firms with poor credit quality (unobserved to econometricians

[30] These informal tests of exclusion restriction are not tabulated to save space. Full results are available upon request.

[31] The self-selection issue of borrowing in concentrated or non-concentrated banking markets is not modeled. This self-selection issue is unlikely to be present because cross-regional loans are rare, due to the segmentation of Chinese banking markets.

but known to competing banks) could only borrow repeatedly from their incumbent banks due to limited outside options. Therefore the positive correlation between relationship lending and collateral could be the result of unobserved poor credit quality instead of informational rent. We employ a recursive bivariate probit model with instrumental variables to address this concern. To implement this approach, firstly, we need to transform our continuous measure of relationship lending into a binary variable. In a fashion similar to Presbitero and Zazzaro (2010), a relationship dependency dummy (Rel) is defined to equal 1 if the firm obtains at least 20% (the sample median of the *Sizeconcen*) of bank loans from the lender prior to the current loan, and 0 otherwise. Secondly, at least one exclusion restriction must be imposed, i.e. there exists at least one exogenous variable that determines Rel, but does not affect $\mathrm{Collateral}$ except through relationship lending. We use past regional average lending rates (*Localavrate*) as instruments (definition and summary statistics are in Table I). A similar approach has been applied in Bharath et al. (2011).[32] *Localavrate* is expected to affect relationship lending positively as firms might prefer to borrow from their relationship lenders when past conditions in regional (local) credit markets are tight. It is unlikely that past regional average lending rates will affect the collateral pledged for current individual loans.[33]

Similar to *Equation (4)*, the recursive bivariate probit model is defined by a two-equation system: a *Collateral Equation* and a *Relationship Equation*, where both relationship dependency dummy Rel and its interaction term with IPO ($Rel * IPO$) enter *Collateral Equation*. Other covariates in the *Collateral Equation* correspond to the ones used in Table IV, Column (3). The model is identified once the exclusion restriction *Localavrate* is added to the *Relationship Equation*, together with other determinants of relationship lending[34]. Results are reported in Table VI, Column (4). The estimated

Regional banks such as city commercial banks and rural commercial (co-operative) banks mainly serve clients located in their own region. It is only recently that some city commercial banks have been allowed to establish branches outside their home province to better serve local customers. Banks that operate at the national level such as state-owned commercial banks (SOCBs) and joint-stock commercial banks (JSCBs) have a wide distribution of branch networks, which allows their local branches to provide loans to local firms. It is unlikely that firms will self-select themselves to borrow from banks (branches) outside their home province or in regional markets characterized by specific market structures in order to avoid collateral requirements.

[32] Bharath et al. (2011) invests joint estimations of loan contract terms, employing lagged average lending spread over the last six month as instrument for collateral. They argue lagged average lending spread do not necessary affect non-price terms such as collateral, based on their conversation with bankers.

[33] Unreported results show *Localavrate* is statistically insignificant as a determinant of collateral incidence. Results are available upon request.

[34] Covariates in the *Relationship Equation* include firm and loan characteristics, monetary policy and regional macroeconomic variables, and fixed effects dummies. Excluding potentially endogenous loan characteristics do not change our results. Estimation of the R*elationship Equation* show firms are more likely to borrow from relationship lenders if they are located in concentrated markets, are liquid, smaller, more leveraged, less profitable, have better loan contract terms such as longer loan maturities and lower spreads, and if the loan represents a relatively large portion of the firm's existing debt (*Loanconcen*). Full

correlation between the error terms of the two equations, i.e. ρ, is significantly negative (-0.508***, p-value is 0.002), rejecting the exogeneity assumption of relationship lending and supporting the recursive bivariate probit estimation approach. The coefficient of the instrumental variable (*Localavrate*) in the *Relationship Equation* is 0.115, significant at 1%, indicating firms in provinces with higher past average lending rates are also more likely to borrow from relationship lenders. Turning to the *Collateral Equation*, the estimates controlling endogeneity of relationship lending are consistent with the baseline results of Column (1).

6. Further robustness tests

This section presents further robustness tests accounting for the unobserved firm specific time-invariant risks with fixed effect logit model (6.1); the endogeneity of other loan contract terms using instrumental (IV) probit model (6.2); and the sensitivity of the results to alternative samples (6.3). Our main results are robust to all these tests.

6.1. Firm fixed effects

Including firm fixed effects alleviates the concern that unobserved time-invariant risk factors can drive our results. As the Probit model is not suitable for fixed effects regressions, we use a fixed effects Logit model. Table VII reports the full sample results for specifications without potentially endogenous loan contract terms (Column (1)) and with those terms (Column (2)). Column (3) and (4) replicate these regressions for a sample excluding loans originated after a firm's bond IPOs. After controlling for firm fixed effects, the impact of relationship intensity on collateral incidence is significantly positive for pre-IPO loans, but is statistically insignificant across all specifications for post-IPO loans (H_0: $Sizeconcen_{il}+Sizeconcen_{il}*IPO_{il}=0$ cannot be rejected). This result is even stronger than that of the baseline model (Column (3) of Table IV), supporting the hypothesis that IPOs as an informational shock eliminates rent extraction opportunities. The results for market concentration are similar to

results of the recursive bivariate probit model are available upon request.

previous findings, i.e. increasing market concentration increases the likelihood of collateral, and this effect is stronger for pre-IPO loans.

6.2. Endogeneity of loan contract terms

In this subsection we apply instrumental variable (IV) Probit regressions to address the endogeneity issue of loan contract terms. We examine two possibilities: exclude *Spread* from the determinants of collateral and treat *Maturity* as the sole endogenous variable; and treat both *Spread* and *Maturity* as endogenous variables.[35] The instruments chosen for *Maturity* are asset maturity (*Amaturity*, Barclay et al., 1995) and term spread (*Termspread*, Dennis et al., 2000) and Brick and Ravid, 1985)). For the lending spread (*Spread*), we use as an instrument the benchmark loan spread (*Benchsprd* = benchmark lending rate minus the benchmark deposit rate), and lagged regional average lending rates (*Localavrate*). *Benchsprd* and *Localavrate* should be correlated with the lending spread but are not likely to be related to whether or not a particular loan is collateralized.[36] Summary statistics and definitions of these instrumental variables are in Panel F of Table I. Technical details, results and the relevance and validity of instrumental variables are reported in the Internet Appendix, Section B and Table IA.V. We find loan contract terms are indeed endogenous as the null hypotheses that *Maturity* alone or *Maturity* and *Spread* together are exogenous are strongly rejected (Wald-test p-value=0.0192 and 0.0000, respectively). Nevertheless, the IV probit results are largely consistent with previous findings, except that $Sizeconcen_{il}$ loses its explanatory power for post-IPO loans ($H_0{:}Sizeconcen_{il}+Sizeconcen_{il}*IPO_{il}=0$ cannot be rejected, p-value=0.99 or 0.86 depending on specifications), which is a even stronger result than for the baseline model. Results for market structure are also similar to previous findings.

[35] The existing literature differs in treating which of the loan contract terms should be endogenous in determining collateral. Dennis et al. (2000) and Bharath et al. (2011) consider *Maturity* as the only endogenous contract term that affects collateral. The underlining assumption is that the lending spread is determined after the decision on collateral pledging. On the other hand, Brick and Paila (2007) and Ono and Uesugi (2009) model the spread as an endogenous determinant of collateral. As empirical validations are provided for both assumptions and theoretical advantages of either assumption are unknown a priori, we examine both.

[36] *Benchsprd* and *Localavrate* may reflect changes in the monetary policy stance or business cycle, which in turn might affect the incidence of collateral. See Jimenez et al. (2006). If this were true, these variables cannot serve as valid instruments. However, our estimations show that monetary conditions measured by the reserve requirement ratio or 7-day repo rate, or the business cycle measured by regional GDP growth rates, do not impact significantly on collateral incidence, as reported in most of our tables.

6.3. Alternative samples

Lastly, we investigate in this section if results from the baseline model are sensitive to alternative samples. First, we focus on a sample of firms that borrowed at least once before its equity IPO and at least once after, which allows us to compare more precisely changes in collateral incidence around IPOs. Second, we restrict the sample to loans that were originated right before and after the IPO (e.g. one loan before and one loan after); four loans closest to IPO dates (e.g. two before and two after); and six loans closest to IPO dates (e.g. three before and three after). These short event windows minimize the possibility that significant events other than IPOs affect our results. Results for these samples are reported in the Internet Appendix, Table IA.VI. Finally, we investigate if our results are driven by non-commercial basis loans. We re-estimate *Equation (3)* by removing progressively loans from policy banks, state-owned banks, trust and investment companies and other financial institutions, on the basis that loans from these institutions could be based on policy preferences, political pressure, or other non-standard credit criteria. Results are reported in the Internet Appendix, Table IA.VII. Our main findings are solid in almost all of these samples.

7. Conclusions

In this paper, we investigate whether proprietary information obtained from both lending relationship and bank market concentration allow for informational rent through collateral. We find collateral incidence increases with both relationship lending and market concentration, and these effects are less pronounced for transparent firms. Using equity IPOs as informational shocks, we find that collateral incidence increases with both relationship intensity and market concentration for pre-IPO loans, while these effects are greatly moderated for post-IPO loans. Furthermore, we demonstrate that following an IPO, rent extraction through collateral is moderated for safe firms but intensified for risky firms, a result in line with the prediction of Rajan (1992). Further robustness tests suggest that our results are not caused by differences in credit risks, the possible endogeneity of IPOs and relationship lending, concurrent lending and underwriting, or non-commercial basis loans. Our results complement the finding that banks extract informational rents by charging higher lending rates (Hale and Santos, 2009; Schenone, 2009), and in part validate the theoretical predictions that concentrated market structure facilitates accumulation of inside information (Dell'Ariccia et al., 1999; Dell'Ariccia, 2001). Finally, we provide the first loan-level analysis on collateral for China, which has received little attention so far.

Our study opens up a few avenues for future research. A cross-country investigation of rent extraction through collateral could be fruitful. Rent extraction through collateral may be more likely to be observed in less developed markets where banks lack sufficient tools to price credit risks. Another possibility is to check if banks choose methods to charge rents (either through lending rates or collateral) depending on price regulation or monetary policy. A third avenue is to investigate how rent extraction through collateral could vary with the legal and institutional environment, as these aspects crucially determine how valuable collateral is to banks. We leave these issues for future research.

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Table I: Summary statistics and variable definition

Variable	Definition	N	Mean	S.D	Min	Max
Panel A: Market structure						
ACR4	The market share (in terms of assets) of the top four banks in the province. Measured at one semi-accounting year prior to current loan.	9288	0.55	0.06	0.35	0.97
Panel B: Firm characteristics						
Size	Natural logarithm of total assets in millions of RMB deflated to year 2006 value. Measured at one semi-accounting year prior to current loan.	8779	7.67	1.16	4.01	12.72
Leverage	Outstanding debt/total assets, measured at one semi-accounting year prior to current loan.	8779	0.56	0.19	0.02	2.37
ROA	Return on assets, measured at one semi-accounting year prior to current loan.	8779	0.06	0.07	-0.44	1.71
Age	Natural log of firm age. Firm age is the difference in months between the firm's establishment date and the loan initiation date.	9288	5.03	0.40	2.77	6.62
Tangibility	(Net property, plants and equipment)/total assets, measured at one semi-accounting year prior to current loan.	8779	0.27	0.19	0.00	0.92
FT	= 1 if majority stake is owned by the State, and 0 otherwise.	9288	0.40	0.49	0	1
Liquidity	Current assets/total assets, measured at one semi-accounting year prior to current loan.	8779	0.55	0.23	0.01	1
Loanconcen	Loan concentration ratio. Defined as Loansize / (Loansize and debt outstanding).	8779	0.04	0.07	0.00	0.93
IPO	= 1 if loan is issued after the IPO, and 0 otherwise.	9288	0.83	0.37	0	1
Panel C: Loan characteristics						
Collateral	= 1 if loan is secured by collateral, and 0 otherwise.	9288	0.66	0.47	0	1
Maturity	Natural log of loan maturity. Measured in months.	9288	3.25	0.79	0.00	5.70
Spread	Difference between lending rate and benchmark deposit rate of corresponding maturity. Measured in percentage.	9288	2.85	1.21	0.71	13.60
Loansize	Natural log of loan size. Measured in millions of RMB deflated to year 2006 value.	9288	3.13	1.41	-3.70	8.97
Panel D: Relationship variables						
Numlender	Number of different lenders the firm has borrowed from prior to origination of current loan.	9288	3.93	3.45	0	28
Sizeconcen	The amount of loans that a firm has borrowed from its current lender as a proportion of the total amount of loans it obtained prior to the current loan.	9288	0.33	0.35	0	1
Numconcen	The number of loans that a firm has borrowed from its current lender as a proportion of the total number of loans it borrowed prior to the current loan.	9288	0.34	0.34	0	1
First	= 1if the current loan is the first loan borrowed from this lender, and 0 otherwise.	9288	0.24	0.43	0	1
Switch	= 1 if the current loan is borrowed from the same lender as the previous loan, and 0 otherwise.	9288	0.40	0.49	0	1
Panel E: Monetary and regional macroeconomic variables						
RRR	Reserve Requirement Ratio for the month when the loan is issued.	9288	0.17	0.03	0.10	0.21
Repo	7-day repo rate for the month when the loan is issued, in percentage.	9288	2.55	1.21	0.94	6.92
CPI	Provincial consumer price index, measured at one semi-account year prior to current loan.	9288	1.03	0.03	0.98	1.10
NPLratio	Provincial non-Performing loan ratio, measured at one semi-account year prior to current loan.	9288	0.03	0.03	0.00	0.21
Realgdpindex	Provincial real GDP growth rate, measured at one semi-account year prior to current loan	9288	0.09	0.03	0.01	0.18

Panel F: Instrumental variables						
Amaturity	((current assets/total assets)*(current assets/cost of goods sold)+(fixed assets/total assets)*(fixed assets/depreciation))/1000	9288	10.68	6.64	0.18	55.33
dd_lag2	The number of CSRC IPO suspension days during the 2-year window prior to listing date.	9288	188.6	168.8	0	523
Affected_Firms	Dummy variable equals 1 if firm experienced at least one CSRC IPO suspension during the 2-year window prior to listing date.	9288	0.68	0.47	0	1
Termspread	Yield difference between 5-year Treasury bond and 1-year Treasury bond, for the month when the loan is issued, in percentage.	9288	0.86	0.44	-0.19	1.54
Localavrate	People's Bank of China reports on a yearly basis the percentage of loans that are issued below/at/above the corresponding benchmark rate. The actual lending rate to benchmark rate ratio is classified in seven groups: [0.9,1], [1], [1.0-1.1], [1.1-1.3],[1.3-1.5],[1.5-2.0] and [above 2.0]. We take the middle value of each group and calculate the weighted average ratio using the percentage of loans within each group as weight. This weighted average is then multiplied with the one-year reference rate to calculate the regional average lending rates. Measured at one semi-account year prior to the current loan. In percentage.	9288	6.79	0.94	5.14	9.88
Benchsprd	Benchmark lending rate minus benchmark deposit rate of corresponding maturity, for the month the loan is issued. In percentage.	9288	2.42	0.55	1.4	3.78
Panel G: Additional variables						
Numalst	Number of analysts following the firms measured at one semi-accounting year before loan origination.	7719	11.01	10.90	0	66
Instishare	Percentage of shares held by institutional investors measured at one semi-accounting year before loan origination, in percentage.	7367	29.07	22.03	0	96.33
Multiapp	Dummy variable that equals 1 if firm applied for its IPO multiple times before eventually listed, and 0 if succeeded in the first IPO application.	9288	0.05	0.22	0	1
Affected_Loans	Dummy variable equals 1 if the loan is borrowed by firms that experienced CSRC IPO suspension during the suspension periods.	9288	0.15	0.36	0	1

Table II: Univariate tests

	Panel A: Sizeconcen			Panel B: ACR4			Panel C: IPO		
	<Median	>=Median	Mean diff	<Median	>=Median	Mean diff	Pre-IPO	Post-IPO	Mean diff
Relationship variables									
Sizeconcen	--	--	--	0.32	0.35	-0.02***	0.40	0.32	0.08***
Numconcen	0.22	0.73	-0.51***	0.33	0.35	-0.02***	0.41	0.33	0.08***
Numlender	4.65	3.21	1.44***	4.41	3.46	0.96***	2.17	4.29	-2.11***
Market structure									
ACR4	0.55	0.55	-0.00*	-	-	-	0.56	0.55	0.01***
Loan characteristics									
Collateral	0.66	0.66	-0.00	0.62	0.70	-0.08***	0.86	0.62	0.24***
Maturity	3.19	3.32	-0.13***	3.26	3.25	0.00	3.12	3.28	-0.16***
Spread	2.99	2.70	0.30***	2.87	2.82	0.04*	2.85	2.85	0.01
Loansize	3.19	3.07	0.12***	3.17	3.10	0.08**	2.32	3.30	-0.97***
Firm characteristics									
FT	0.42	0.39	-0.03**	0.42	0.39	0.03***	0.11	0.46	-0.35***
Liquidity	0.55	0.54	0.01*	0.60	0.50	0.10***	0.58	0.54	0.04***
Total Assets	7.76	7.58	0.18***	7.81	7.53	0.28***	6.32	7.85	-1.53***
Leverage	0.57	0.55	0.02***	0.55	0.57	-0.02***	0.55	0.56	-0.00
ROA	0.07	0.06	0.00	0.06	0.07	-0.00	0.15	0.05	0.09***
Age	5.04	5.02	0.02***	5.06	5.00	0.06***	4.70	5.10	-0.40***
Tangibility	0.27	0.27	-0.01*	0.24	0.31	-0.07***	0.27	0.27	-0.01

*** p<0.01, ** p<0.05, * p<0.1.

Table III: Collateral determinants and borrower information transparency

Panel A shows the results for the estimation of *Equation (1)*. M.E are the marginal effects calculated on the basis of the results in Column (1). Panel B estimates *Equation (2)*. It reports the impact of $Sizeconcen_{il}$ and $ACR4_{il}$ on collateral incidence differentiated by the informational transparency of borrowers ($Infor_{il}$), which is defined by three proxies: *Borrower ownership* (*FT*=1 if state owned and 0 otherwise); *Listed Board* (*Listmain*=1 if listed in the main board and 0 otherwise); and *Firm Size* (*Medianta*=1if *log(total assets)* is above the provincial median and 0 otherwise). Panel C estimates *Equation (2)* using stock market information production (*Numalst* and *Instishare*) as measures of informational transparency of borrowers. The sample is restricted to post-IPO loans for Column (6) and (7). In all panels, the control variables include firm characteristics, loan contract terms, monetary policy variables, regional macroeconomic variables and a set of fixed effects, including *Industry, Province, Banktype* and *Loan-year* dummies. In column (2), *Maturity* and *Spread* are excluded for endogeneity concerns. Removing these terms in Panel B and C do not affect our results, which are available upon request. Results for fixed effects dummies are not reported to save space. The equations are estimated with the Probit model. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A: Main Effects			Panel B: Borrower Information Transparency			Panel C: Stock Market Infor Production	
	With contract terms	Without contract terms	M.E of model (1) (%)	Board of listing	Ownership	Firm size	Numalst	Instishare
VARIABLES	(1)	(2)		(3)	(4)	(5)	(6)	(7)
Sizeconcen	0.153**	0.170**	1.40	0.231***	0.256***	0.287***	0.209**	0.277***
	(0.068)	(0.068)		(0.085)	(0.082)	(0.076)	(0.088)	(0.097)
ACR4	2.685***	2.623***	4.45	3.826***	3.463***	3.482***	4.912***	4.897***
	(0.805)	(0.802)		(0.895)	(0.858)	(0.832)	(0.901)	(0.924)
Listmain*Sizeconcen				-0.129				
				(0.098)				
FT*Sizeconcen					-0.203**			
					(0.098)			
Medianta*Sizeconcen						-0.390***		
						(0.102)		
Numalst*Sizeconcen							-0.010**	
							(0.005)	
Instishare*Sizeconcen								-0.770***
								(0.240)
Listmain*ACR4				-1.664***				
				(0.616)				
FT*ACR4					-1.603***			
					(0.619)			
Medianta*ACR4						-2.051***		
						(0.571)		
Numalst*ACR4							-0.149***	
							(0.032)	
Instishare*ACR4								-4.924***
								(1.318)
Listmain				0.705**				
				(0.346)				
Medianta						1.334***		
						(0.316)		
Numalst							0.074***	
							(0.017)	
Instishare								2.574***
								(0.722)
FT	-0.606***	-0.594***	-16.7	-0.565***	0.335	-0.618***	-0.597***	-0.568***
	(0.047)	(0.046)		(0.048)	(0.340)	(0.047)	(0.050)	(0.050)
First	0.036	0.049	0.94	0.048	0.044	0.019	-0.030	-0.042
	(0.056)	(0.055)		(0.056)	(0.056)	(0.056)	(0.059)	(0.059)
Switch	-0.028	-0.064	-0.75	-0.033	-0.028	-0.023	-0.020	-0.023

	(0.039)	(0.039)		(0.040)	(0.039)	(0.039)	(0.042)	(0.042)
IPO	-0.412***	-0.387***	-10.39	-0.322***	-0.391***	-0.405***		
	(0.071)	(0.071)		(0.073)	(0.071)	(0.071)		
Numlender	0.024***	0.018**	2.13	0.021***	0.024***	0.020***	0.027***	0.024***
	(0.007)	(0.007)		(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Liquidity	-0.458***	-0.545***	-2.76	-0.504***	-0.447***	-0.375**	-0.558***	-0.689***
	(0.155)	(0.153)		(0.156)	(0.155)	(0.155)	(0.168)	(0.167)
Size	-0.221***	-0.215***	-7.29	-0.191***	-0.222***	-0.233***	-0.163***	-0.217***
	(0.027)	(0.027)		(0.028)	(0.027)	(0.030)	(0.033)	(0.030)
Leverage	0.941***	1.049***	4.53	1.040***	0.926***	0.951***	0.891***	0.963***
	(0.127)	(0.126)		(0.129)	(0.127)	(0.127)	(0.138)	(0.137)
ROA	-1.134***	-1.084***	-2.22	-1.124***	-1.102***	-1.160***	-0.583*	-0.704**
	(0.277)	(0.282)		(0.279)	(0.278)	(0.276)	(0.330)	(0.325)
Age	-0.415***	-0.432***	-4.50	-0.331***	-0.419***	-0.409***	-0.385***	-0.422***
	(0.058)	(0.057)		(0.060)	(0.058)	(0.058)	(0.064)	(0.064)
Tangibility	-0.852***	-0.891***	-4.43	-0.893***	-0.855***	-0.782***	-1.028***	-1.021***
	(0.179)	(0.178)		(0.180)	(0.179)	(0.179)	(0.189)	(0.188)
Maturity	0.169***		3.39	0.169***	0.169***	0.171***	0.187***	0.200***
	(0.028)			(0.028)	(0.028)	(0.028)	(0.030)	(0.030)
Spread	0.031*		1.00	0.036**	0.031*	0.035**	0.021	0.023
	(0.017)			(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
Loansize	-0.089***	-0.070***	-3.37	-0.090***	-0.090***	-0.090***	-0.095***	-0.095***
	(0.020)	(0.020)		(0.020)	(0.020)	(0.020)	(0.021)	(0.021)
Loanconcen	1.830***	1.921***	3.37	1.956***	1.804***	1.866***	1.779***	1.672***
	(0.413)	(0.408)		(0.410)	(0.414)	(0.415)	(0.440)	(0.434)
RRR	-0.071	-0.021	-0.05	0.050	-0.202	-0.188	0.645	0.422
	(2.902)	(2.884)		(2.909)	(2.904)	(2.907)	(3.068)	(3.068)
Repo	0.048*	0.045*	1.51	0.044	0.048*	0.050*	0.054*	0.047*
	(0.027)	(0.027)		(0.027)	(0.027)	(0.027)	(0.029)	(0.029)
CPI	1.475	2.003	1.04	1.241	1.320	1.518	2.608	2.614
	(1.510)	(1.501)		(1.514)	(1.513)	(1.513)	(1.601)	(1.597)
NPLratio	-0.535	-0.647	-0.42	-0.305	-0.526	-0.685	-0.414	-0.121
	(1.135)	(1.132)		(1.137)	(1.135)	(1.140)	(1.183)	(1.179)
Realgdpindex	1.097	1.548	1.00	0.763	0.787	0.975	1.606	1.198
	(1.435)	(1.429)		(1.441)	(1.442)	(1.439)	(1.500)	(1.496)
Constant	-0.566	-0.644		-1.577	-0.850	-1.123	-7.478	-6.924
	(1.874)	(1.869)		(1.888)	(1.879)	(1.884)	(106.776)	(106.273)
Observations	8,741	8,753		8,741	8,741	8,741	7,620	7,620
Pseudo R2	0.287	0.283		0.289	0.288	0.290	0.291	0.291
H_0:Sizeconcen+Infor*Sizeconcen=0				0.102	0.052	-0.103		
H_0: ACR4+Infor*ACR4=0				2.162***	1.860**	1.431		

Table IV: Identify informational rents through IPOs

This table reports estimates based on various versions of *Equation (3)*. Column (1) to Column (3) add the interaction terms $Sizeconcen_{il}*IPO_{il}$ and $ACR4_{il}*IPO_{il}$ progressively. Column (4) excludes the potentially endogenous contract terms *Spread* and *Maturity* and re-estimates Column (3). M.E. are marginal effects based on Column (3). For variables interacting with IPO_{il}, we report marginal effects of said variable from before and after the IPO. Results for control variables and fixed effects dummies are not reported to save space. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1)	(2)	(3)	(4)	M.E. of Model (3)
Sizeconcen	0.493**	0.169**	0.596***	0.604***	4.78
	(0.215)	(0.069)	(0.218)	(0.218)	
ACR4	2.806***	5.617***	5.935***	5.931***	8.51
	(0.807)	(1.201)	(1.216)	(1.211)	
Sizeconcen*IPO	-0.369		-0.471**	-0.463**	1.17
	(0.226)		(0.229)	(0.228)	
ACR4*IPO		-3.218***	-3.503***	-3.574***	4.15
		(1.000)	(1.016)	(1.012)	
First	0.423**	0.203	0.478**	0.462**	10.78
	(0.194)	(0.143)	(0.195)	(0.195)	
First*IPO	-0.430**	-0.190	-0.485**	-0.454**	-0.19
	(0.201)	(0.144)	(0.203)	(0.203)	
Switch	0.177	0.153	0.175	0.133	4.14
	(0.126)	(0.126)	(0.126)	(0.126)	
Switch*IPO	-0.218*	-0.189	-0.215	-0.207	-1.06
	(0.132)	(0.132)	(0.132)	(0.132)	
Numlender	-0.000	-0.023	0.009	-0.002	0.78
	(0.033)	(0.028)	(0.033)	(0.033)	
Numlender*IPO	0.025	0.051*	0.016	0.021	2.34
	(0.034)	(0.029)	(0.034)	(0.034)	
IPO	-0.132	1.396**	1.914***	1.951***	-7.13
	(0.206)	(0.572)	(0.627)	(0.626)	
Constant	-1.063	-2.417	-2.936	-3.025	
	(1.886)	(1.946)	(1.964)	(1.959)	
Fixed effects dummies	Industry, Province, Bank Type, Time				
Other loan contract terms	Yes	Yes	Yes	No	
Controls variables	firm characteristics, monetary policy and regional macro variables				
Observations	8,741	8,741	8,741	8,753	
Pseudo R2	0.288	0.289	0.289	0.285	
H_0:Sizeconcen+Sizeconcen*IPO=0	0.124*		0.124*	0.141**	
H_0: ACR4+ACR4*IPO=0		2.399***	2.431***	2.357***	
H_0:First+First*IPO=0	-0.007	0.013	-0.007	0.008	
H_0:Switch+Switch*IPO=0	-0.041	-0.036	-0.039	-0.074*	

Table V: Informational rents and firm risk

This table investigates how informational rents vary with firm risk. Firm risk is proxied by a dummy variable *Multiapp* that equals one if the firm applied multiple times before eventually being listed, and zero if being listed in its first IPO application. Column (1) tests the main effect of *Multiapp*. Column (2) introduces three-way interaction terms among informational rent variables (*Sizeconcen* and *ACR4*), listing status (*IPO*) and *Multiapp*. For these two columns, other control variables are the same as in Table III (Column (1)). Column (3) and (4) removes progressively loan contract terms and monetary and regional macroeconomic variables. Results of control variables and fixed effects dummies are not reported to save space. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1)	(2)	(3)	(4)
Sizeconcen	0.600***	0.634***	0.648***	0.646***
	(0.219)	(0.225)	(0.225)	(0.225)
ACR4	5.979***	6.073***	6.081***	5.741***
	(1.217)	(1.254)	(1.249)	(1.226)
Sizeconcen*IPO	-0.476**	-0.532**	-0.526**	-0.526**
	(0.229)	(0.236)	(0.235)	(0.235)
ACR4*IPO	-3.558***	-4.368***	-4.441***	-4.419***
	(1.016)	(1.060)	(1.055)	(1.054)
Multiapp	0.286***	0.730	0.925	0.820
	(0.094)	(2.131)	(2.093)	(2.098)
Sizeconcen*Multiapp		-0.462	-0.497	-0.510
		(0.471)	(0.465)	(0.465)
ACR4*Multiapp		-1.493	-1.856	-1.647
		(3.676)	(3.608)	(3.617)
Multiapp*IPO		-4.872**	-4.873**	-4.791**
		(2.364)	(2.327)	(2.331)
Sizeconcen*Multiapp*IPO		0.944*	0.959*	0.974*
		(0.552)	(0.546)	(0.546)
ACR4*Multapp*IPO		9.315**	9.305**	9.143**
		(4.085)	(4.019)	(4.026)
IPO	1.962***	2.347***	2.384***	2.379***
	(0.627)	(0.650)	(0.647)	(0.647)
Constant	-2.854	-2.794	-2.904	-0.632
	(1.963)	(1.972)	(1.967)	(0.925)
Fixed effects dummies	Industry, Province, Bank Type, Time			
Firm characteristics	Yes	Yes	Yes	Yes
Other loan contract terms	Yes	Yes	No	No
Monetary policy variables	Yes	Yes	Yes	No
Regional macro variables	Yes	Yes	Yes	No
Observations	8,741	8,741	8,753	8,753
Pseudo R2	0.290	0.293	0.289	0.289

Table VI: Bivariate Probit Models

This table reports the results of recursive Bivariate Probit models with instrumental variables. Column (1) replicates the Probit model results of Table IV, column (3) for comparison purposes. Column (2) and (3) treat *IPO* as endogenous variable. Column (4) treats relationship lending dummy *Rel* as endogenous variable, where *Rel* is a dummy variable equals 1 if the firm obtains at least 20% (i.e. the sample median of the *Sizeconcen*) of bank loans from the lender prior to the current loan, and 0 otherwise. In all specifications, the variables in the *Collateral Equation* correspond to the ones used in Table IV, column (3), except that in Column (4) where *Sizeconcen* and *Sizeconcen*IPO* are replaced by *Rel* and *Rel*IPO*, respectively. Variables in the *IPO Equation* include one instrument (*Affected_Firms* or *Log(1+dd_lag2)*) and all variables in the *Collateral Equation*, except *IPO* and its interaction terms with other covariates. Variables in the *Relationship Equation* include one instrument (*Localavrate*) and all variables in the *Collateral Equation*, except *Rel*, *Rel*IPO*, relationship control variables (*Relcontrols* defined in section 2.1.1), and their interactions with *IPO*. The instrumental variables are defined as following: *Affected_Firms* is a dummy variable equals 1 if the firm has experienced at least one CSRC IPO suspension within the 2-year window prior to the firm's actual listing; *Log(1+dd_lag2)* is the logarithm of 1 plus the number of CSRC IPO suspension days within the 2-year window prior to the firm's actual listing; *Localavrate* is the regional average lending rate one semi-accounting year before the current loan. Full results of Bivariate Probit models are available upon request. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Probit	Bivariate probit		Bivariate Probit
		IPO as endogenous		*Rel* as endogenous
		IV: Affected_Firms	IV: Log(1+dd_lag2)	IV: Localavrate
VARIABLES	(1)	(2)	(3)	(4)
Collateral Equation				
Sizeconcen (Rel)	0.596***	0.589***	0.589***	1.314***
	(0.218)	(0.217)	(0.217)	(0.247)
ACR4	5.935***	5.873***	5.848***	4.999***
	(1.216)	(1.214)	(1.214)	(1.178)
Sizeconcen*IPO (Rel*IPO)	-0.471**	-0.460**	-0.460**	-0.521***
	(0.229)	(0.228)	(0.228)	(0.148)
ACR4*IPO	-3.503***	-3.487***	-3.469***	-3.198***
	(1.016)	(1.013)	(1.012)	(0.935)
IPO Equation				
Affected_Firms		-0.681***		
		(0.094)		
Log(1+dd_lag2)			-0.080***	
			(0.016)	
Relationship Equation				
Localavrate				0.115***
				(0.040)
ρ		-0.129 (p=0.12)	-0.114 (p=0.17)	-0.508***(p=0.002)
Observations	8741	8,765	8,765	8765

Table VII: Firm fixed effects

This table reports the results for the fixed effects Logit model for alternative samples, and for specifications with and without loan contract terms. Results for firm characteristics and fixed effects dummies are not reported to save space. Monetary policy variables and regional macro variables are not included in this estimation. Including them does not change our results. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Fixed effects Logit model			
	All loans		*Loans originated before corporate bond IPOs*	
	Without loan contract terms	With loan contract terms	Without loan contract terms	With loan contract terms
VARIABLES	(1)	(2)	(3)	(4)
Sizeconcen	1.645***	1.634***	1.750***	1.713***
	(0.543)	(0.544)	(0.542)	(0.543)
ACR4	23.247***	24.007***	23.356***	24.055***
	(5.305)	(5.284)	(5.337)	(5.309)
Sizeconcen*IPO	-1.472***	-1.453**	-1.774***	-1.722***
	(0.564)	(0.565)	(0.567)	(0.568)
ACR4*IPO	-17.824***	-18.051***	-19.251***	-19.548***
	(5.210)	(5.177)	(5.209)	(5.169)
First	1.074***	1.080***	1.292***	1.287***
	(0.389)	(0.388)	(0.397)	(0.395)
First*IPO	-1.209***	-1.199***	-1.547***	-1.527***
	(0.400)	(0.399)	(0.410)	(0.408)
Switch	0.407	0.448	0.325	0.374
	(0.300)	(0.299)	(0.303)	(0.302)
Switch*IPO	-0.472	-0.476	-0.365	-0.368
	(0.311)	(0.310)	(0.316)	(0.315)
Numlender	0.023	0.033	0.063**	0.075**
	(0.028)	(0.029)	(0.030)	(0.030)
IPO	10.171***	10.272***	10.954***	11.097***
	(2.978)	(2.959)	(2.978)	(2.954)
Observations	5,856	5,851	4,816	4,811
Number of firms	291	291	255	255
Pseudo R2	0.137	0.142	0.138	0.144
H_0:Sizeconcen+Sizeconcen*IPO=0	0.173	0.181	-0.024	-0.009
H_0: ACR4+ACR4*IPO=0	5.423***	5.967***	4.105*	4.506*