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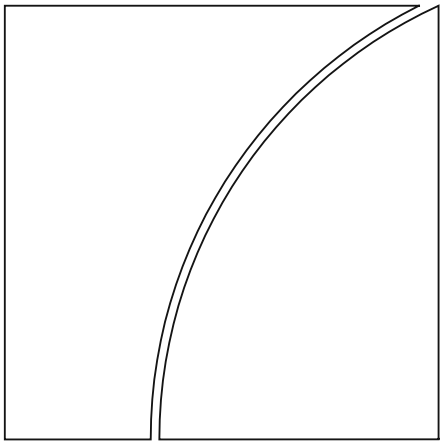

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by Bing Xu, Honglin Wang, Adrian van Rixtel

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Do banks extract informational rents through collateral?[1]

Bing Xu, Honglin Wang, Adrian van Rixtel[2]

Abstract

This paper investigates if informational monopolies resulting from relationship lending and bank market concentration allow for rent extraction through collateral. Our identification strategy hinges on the notion that informational equalization shocks (such as equity IPOs) erode rent seeking opportunities, while competing theories do not rely on information asymmetries among lenders. Using a unique hand-collected database of 9,288 bank loans obtained by 649 listed Chinese firms, we find that collateral incidence is positively associated with relationship intensity and bank market concentration, while this effect is moderated for post-IPO loans. These results are obtained controlling for a large number of loan and firm characteristics, monetary policy variables and regional macroeconomic characteristics. We also demonstrate important cross-sectional variation among borrowing firms: rent extraction through collateral is significantly less pronounced for less risky firms. Our results hold for a battery of robustness tests, both included in the paper and in an Internet appendix (available upon request). Furthermore, we provide new evidence on the determinants of collateral in Chinese bank lending markets.

JEL Classification: G21, L11.

Keywords: Informational rents, collateral, relationship lending, market structure, IPOs, China.

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1. Introduction

Banks accumulate proprietary information about borrowers through their lending, which creates informational asymmetries between "inside" banks that are already lending to a firm and "outside" banks that currently are not (Santos and Winton, 2008). Inside banks may use their informational monopoly to better evaluate firms in ex-ante screening and ex-post monitoring (Boot and Thakor, 1994). This "information accumulation" view of relationship lending suggests that, as a result, borrowers may obtain better conditions, such as a lower lending rate or less stringent collateral requirements. Hence, relationship intensity is negatively correlated with collateral incidence, as they are substitutes for dealing with information opaqueness. Many empirical studies support this hypothesis (e.g. Petersen and Rajan, 1995; Berger and Udell, 1995; Jimenez et al., 2006; Chakraborty and Hu, 2006; Brick and Palia, 2007; Bharath et al., 2011). In contrast, informational advantages linked to relationship lending may be used to "hold up" borrowers (Sharpe, 1990; Rajan, 1992). Firms will face a cost of borrowing from inside banks that is higher than that from outside banks, due to adverse selection. Empirical validations of this informational rent extraction in the relationship lending literature mainly focus on lending rates (see e.g. Hale and Santos, 2009; Schenone, 2010), while rent extraction operating through non-price terms has been left largely unexplored. In this paper, we seek empirical evidence for informational rent extraction through collateral.

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).[3] 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 collateral is valuable to banks not only should debtors default, but at all stages of the lending process. In this context, a natural question is whether informational advantages of relationship banks allow for higher incidence of collateral, implying that collateral can serve as an informational rent seeking channel. In our view, the important role of collateral warrants an in-depth empirical analysis of its potential use in charging rents from borrowers.

Rent extraction is only one of several theories that could explain why collateral incidence and relationship lending may be positively associated. Firstly, Longhofer and Santos (2000) suggest that pledging collateral improves the seniority of the 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] In this context, collateral and relationship intensity could be positively related. Secondly,

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

[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.

Dewatripont and Maskin (1995) highlight another potential cost of relationship lending, which hinges on the observation that relationship banks have difficulties in enforcing loan liquidation when borrowers face financial distress. This problem arises because relationship lenders have the incentive to extend further credit in the hope of recovering loans granted previously. Anticipating the ex-post realization of this "soft budget constraint", the borrower is not sufficiently incentivized to make an effort ex-ante to prevent this adverse outcome ex-post. One solution for the soft budget constraint problem is to post collateral (Boot, 2000), which implies a positive correlation between relationship intensity and collateral incidence. Lastly, banks have an interest in extending relationship length (intensity) so as to minimize the per unit fixed costs associated with the evaluation and monitoring of collateral ("cost minimization incentive") (Menkhoff et al., 2006). This de facto produces a positive correlation between collateral and relationship duration (intensity). To the best of our knowledge, no attempt has been made yet to differentiate informational rent seeking from these alternative theories, which all predict that relationship lending and collateral incidence are positively associated.[5]

In addition to relationship lending, we empirically investigate if concentrated bank market structure also promotes informational rent extraction. Similar to relationship lending, the structure of bank lending markets affects the asymmetric distribution of firm-specific information among lenders as well (e.g. Dell'Ariccia, 2001; Marquez, 2002; Dell'Ariccia and Marquez, 2006; Hauswald and Marquez, 2006), which in turn may interact with banks' strategic behavior in determining lending policies and standards (Dell'Ariccia and Marquez, 2006).

To develop our arguments, we rely on a sequence of theoretical advances that relate market structure to the information distribution among lenders.[6] First, information extraction is likely to be less effective in markets composed of many small banks compared to those with only a few large banks (Marquez, 2002). Concentrated markets also lead to better protection of proprietary information from spilling over to competitors, as banks with larger market shares have higher incentives and capacity to maintain this informational advantage. Therefore, concentrated lending markets consolidate not only market shares, but also proprietary information about borrowers. Second, different market structures, which are associated with different implied levels of competition, may also affect the incentive of banks to accumulate information. Increased competition reduces the rents banks can extract, hence decreases the incentives to generate information through credit evaluation (Hauswald and Marquez, 2006). More outside borrowing options for firms in less concentrated markets also inhibit the (re)usability of

[5] Menkhoff et al. (2006) conclude that this positive relation is presumably caused by the "hold-up" of borrowers or cost minimization incentives. Ono and Uesugi (2009) attribute their finding to both the "hold-up" and "soft budget" constraint hypotheses, while Elsas and Krahnen (2000) resort to Longhofer and Santos (2000) to explain why house banks require more collateral.

[6] We restrict ourselves mainly to theories that relate bank market structure to information asymmetry among lenders. Other theories (not crucially related to information asymmetry among lenders) also provide some predictions. For instance, Manove et al. (2001) propose a "lazy bank" model in which banks choose between screening the borrower or asking for collateral. They argue that intensified competition would favor bank laziness in the form of 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 demanded 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.

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).[7] Third, firms are also likely to borrow more often from the same inside lender in concentrated markets, due to more limited options to obtain credit from competing banks. These repeated transactions allow the inside bank to accumulate more private information about the borrower and enjoy an informational monopoly. Lastly, consolidation of proprietary information in concentrated markets deters the entry of new banks, as new entrant banks face larger adverse selection problems, while borrowing firms face higher costs of switching to "de novo" banks. 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).

The aforementioned arguments suggest that concentrated lending markets allow for a more efficient extraction of private information and provide stronger incentives along a number of dimensions. "Inside" banks are incentivized to obtain information; to offer better protection of this information from spilling over to competitors (outside banks); to deter entry of competitors, and to reinforce their information monopolies. A straightforward implication is that concentrated markets could also facilitate informational rent extraction, for example through collateral. The role of market structure in extracting informational rents, however, receives very little attention in the empirical literature, which focuses mostly on the role of relationship lending (see e.g. Schenone, 2010). Rent extraction through informational monopolies existing in concentrated markets suggests a positive correlation between market concentration and collateral incidence. At the same time, this positive relationship may also be explained by alternative hypotheses. In particular, banks can exploit their sheer market power in concentrated markets by imposing more stringent collateral requirements (Hainz, 2003; Berlin and Butler, 2002).

In this paper, we combine the various strands in the literature and investigate empirically whether banks with informational monopolies, either stemming from relationship lending or concentrated market structures, extract informational rents through collateral. This research agenda poses an identification challenge, i.e. how to differentiate informational rent seeking from the competing theories which also predict a positive correlation between either relationship intensity or market structure and collateral incidence. We are able to distinguish the former from the latter, since informational rent extraction depends crucially on information asymmetries existing among inside and outside lenders, while this precondition is not conducive to the core argument in the alternative theories. This 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 equalizes borrower information between inside and outside banks. If this moderation effect is not validated empirically, one can reject the informational rent hypothesis and attribute the higher incidence of collateral of inside banks to competing interpretations.

To this end, we follow Schenone (2010) and introduce the equity IPO of borrowing firms as such a shock. Santos and Winton (2008) and Hale and Santos

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

(2009) use also an informational equalization shock based on IPOs, but they look at initial public offerings of corporate bonds (i.e. when a firm issues for the first time in the public bond market). Also, these three papers investigate informational rent extraction through lending rates. In contrast, our paper is the first to apply equity IPOs to identify if banks charge informational rents through collateral.

Unlike most studies that employ data for advanced economies, our testing ground is China, the largest banking market among emerging market economies. Chinese bank lending markets offer an ideal case for testing informational rent extraction through collateral for several reasons. First, China is a bank-based economy that for many years was characterized by strict interest rate controls, many of which still remain in place 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 over 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 them a valid choice as an exogenous informational equalization shock, as we shall explain later in more detail. In addition, by investigating Chinese loan markets, we contribute to the limited literature on the determinants of collateral in emerging markets in general and in China in particular.

We test the informational rent hypothesis by using a unique hand-collected loan level database of listed firms at the Shenzhen Stock Exchange for the period of 2007-2013. Since listed firms are generally large and old, information about these firms will be more symmetrically distributed among inside and outside lenders, suggesting that informational rents may be more difficult to detect for this sample than for one of smaller firms. Hence, if we were to find evidence of rent extraction through collateral for this sample, it would be a particularly convincing result.[8]

This article reports five main findings. First, we find that both high relationship intensity and concentrated market structures are associated with higher incidence of collateral, and that this effect is stronger for informational opaque borrowers.

Second, when applying IPOs as an informational equalization shock, we find for pre-IPO originated loans that the likelihood of collateralization is increasing with relationship intensity. Once the informational advantage of relationship lenders is eroded after the IPO, however, relationship intensity has a much smaller impact on collateral demanded for post-IPOs 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 for post-IPOs loans, we do not find a similar pattern for collateral. The relatively low degree of competitiveness of the Chinese banking sector relative to that in the United States might explain this result.[9]

[8] 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.

[9] 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

Third, the likelihood of collateral increases with the degree of market concentration both before and after the IPO, but the impact of market concentration is much smaller 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 when information is equalized among inside and outside lenders after the IPO. 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, we also demonstrate important cross-sectional variation among borrowers. Namely, rent extraction through collateral is significantly less pronounced for less risky firms. We find that inside banks strengthen their monopoly power for risky firms after the IPO, while they extract fewer informational rents from safer firms after the IPO.

Finally, our results for the control variables add to the literature on the determinants of collateral, and provide new insights on the drivers of collateral incidence in Chinese bank lending markets in particular.[10] We find that firms with higher credit risk are more likely to pledge collateral, consistent with the "observed-risk" hypothesis (e.g. Boot et al., 1991; Boot and Thakor, 1994). Furthermore, private ownership is associated with a much higher probability of pledging collateral, presumably because implicit guarantees from the state provide an alternative risk-mitigating mechanism to collateral for state-owned firms. In other words, our findings suggest that private firms are financially discriminated against in terms of collateral requirements in China.

We test the validity of important assumptions that underlie our research and identification strategies. One assumption is that a firm's equity IPO reduces information asymmetries between inside and outside lenders, i.e. a stock exchange listing provides additional information about this firm to all competing banks. Our results indicate that banks are less likely to demand collateral when more information is produced by the stock market, indicating banks do take into account additional information from the stock market when granting loans. Furthermore, the ability of inside banks to charge informational rents decreases with the level of stock market information production. Another assumption is that the equity IPO of a firm is an exogenous shock to bank loans. We argue that this can be assumed for China, given the specific peculiarities of the IPO process in this country.

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.

[10] Very few studies have investigated the determinants of collateral in China. Firth et al. (2012) investigate the use of collateral as a governance mechanism as well as its determinants, using firm-level data for a sample of Chinese listed firms. These authors confirm that collateral in China mainly solves moral hazard problems and that state ownership reduces collateral incidence. Chen et al. (2013) study the relationship between collateral and accounting conservatism for a sample of Chinese firms. However, none of these studies investigates the determinants of collateral at the loan-level and pays 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.

We test whether alternative explanations other than informational rent extraction are able to explain our results. Both "bank seniority theory" and "soft-budget constraint theory" highlight the possibility that relationship lenders require less collateral when firms become financially healthier. If firms improve their performance substantially after an IPO, or if relationship dependent and non-dependent firms experience heterogeneous firm-risk dynamics around an IPO, the moderated effect of relationship lending on collateral for post-IPO loans could also be explained by these theories. We do not find evidence to support these explanations. Another possible explanation is that banks exchange better loan conditions (less likelihood of collateral) for corporate bond underwriting business. 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 in underwriting bond IPOs. We find this hypothesis cannot explain the results as well as the rent-extraction hypothesis.

Our results hold after controlling for a broad set of firm and loan characteristics, monetary policy variables, and regional macroeconomic characteristics, as well as industry, provincial, bank-type and time fixed effects. Furthermore, we conduct a battery of further robustness tests to address the following issues: controlling for unobserved firm risks with firm fixed effects; self-selection of relationship lending; sensitivity of our results to alternative samples; and the endogeneity of loan contract terms. These tests do not affect our results. Our results also hold when we use an alternative indicator for relationship intensity. Finally, to investigate if our results are sensitive to legal and institutional characteristics, we further control for these factors in a set of unreported robustness tests.[11] These tests also 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 reports the results of various robustness tests. Finally, Section 6 concludes. Additional results can be found in an Internet Appendix to this paper.

2. Methodology and data

2.1. Methodology

Our main focus is to test whether banks with informational advantages, either stemming from relationship lending or concentrated market structures, are more likely to request collateral. In other words, we explore if banks with informational monopolies extract informational rents through collateral. To that extent, we have developed the following methodology. First, we investigate whether relationship lending and market structure affect collateral incidence positively. Second, we explore whether the informational transparency of firms drives collateral incidence in relation to relationship lending intensity and market structure, in order to assess

[11] Empirical studies have found that banks are better able to control for credit risk if legal frameworks allow lenders to seize collateralized assets in times of default (Aghion and Bolton, 1992; Qian and Strahan, 2007).

if information asymmetries play a role at all. Third, as we intend to use equity IPOs as informational equalization shocks, we investigate whether stock exchange listings in China produce additional information that reduces information asymmetries between inside and outside lenders. Fourth, we use equity IPOs to identify informational rent extraction linked to relationship lending and market structure. Finally, we investigate whether informational rent extraction varies with firm risk.

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 we 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. Also 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. 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.

In order to test these hypotheses, we estimate the following Probit model:

$$\mathrm{P}(\mathrm{Collateral}_{\mathrm{il}}) = \mathrm{F}\big(\beta_0 + \beta_1 \mathrm{Sizeconcen}_{\mathrm{il}} + \beta_2 \mathrm{ACR4}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \sigma_{\mathrm{j}} \mathrm{Relcontrols}_{\mathrm{il}} + \rho \mathrm{IPO}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \varphi_{\mathrm{j}} \mathrm{FC}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \theta_{\mathrm{j}} \mathrm{LC}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \gamma_{\mathrm{j}} \mathrm{MC}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \delta_{\mathrm{j}} \mathrm{RC}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \alpha_{\mathrm{j}} \mathrm{FE}_{\mathrm{il}}\big) \quad (1)$$

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.

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 borrowed from its current lender as a proportion of the total amount of loans which the firm obtained prior to the current loan.[12] By definition, $Sizeconcen_{il}$ takes values between zero and

[12] We employ another relationship measure, Numconcenil, 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 further robustness check. Our main results are not sensitive to this alternative measure. Results are available upon request. The implicit assumption of $Numconcen_{il}$ is that the inside lender is more informed than outside lenders if the firm borrows

one. Borrower i is more dependent on the lender if $Sizeconcen_{il}$ is closer to one. This measuring of relationship lending essentially takes into account what the relative importance of a lender is to the borrower, compared to other lenders.

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 percentage of total assets of all banks in each province.[13] There are 32 provinces in mainland China, which is the lowest level of geographic markets for which disaggregated banking data are available. We treat each province as a separate banking market.

In our analysis, we concentrate on the coefficients of $Sizeconcen_{il}$ and $ACR4_{il}$. Positive coefficients of β_1 and β_2 imply that loans granted by relationship lenders and in concentrated markets are more likely to be collateralized, although this result does not imply informational rent extraction per se. A negative sign of $\beta_1$would support the information accumulation view of relationship lending.

The next set of controls $Relcontrols_{il}$ accounts for additional features of relationship lending that can affect collateral incidence. $Numlender_{il}$ measures the number of different lenders of firm i prior to the current loan. This 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. $First_{il}$ is a dummy variable that equals one if the current loan l is the first loan that the firm obtained from the lender. Collateral requirements for the first loan are likely to be different from those for subsequent loans. $Switch_{il}$ is a binary variable that equals one if the current lender is different from the previous one and zero otherwise. $Switch_{il}$ does not represent the termination of a lending relationship, but merely shows if a borrower switched to another bank at some point in time. 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.

Other control variables include a dummy variable IPO_{il} that equals one if a loan is issued after the borrower's IPO, and zero otherwise, and a set of firm characteristics FC_{il}. 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}; and tangible assets over total assets, $Tangibility_{il}$. We also control for loan concentration at firm i by including the variable $Loanconcen_{il}$, measured as the size of loan l over the sum of the size of loan l and the amount of debt outstanding prior to the origination of loan l. A higher value of this variable indicates that loan l represents a relatively large portion of firm's i debt. Another firm characteristic that is particularly important for China is firm ownership, which is incorporated by the

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 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.

[13] For our purpose, 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).

dummy variable FT_{il}. This variable equals one if the Chinese State is the majority owner and zero if majority ownership lies in the private sector.

Our next set of controls LC_{il} covers loan characteristics that are likely to affect collateral incidence, such as the maturity of loan l in (log) months, $Maturity_{il}$; its (log) size in real terms, $Loansize_{il}$; 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, ($Repo_{il}$), whereas regional macro-economic controls are the real GDP growth rate, $Realgdpindex_{il}$; non-performing loan ratio, $NPLratio_{il}$; and consumer price index, CPI_{il}, all at the provincial level.

The last set of controls are fixed effects (FE_{il}) for time (*Time*), bank-type (*Banktype*), province (*Prov*) and industry-type (*Indu*). Time fixed effects capture differences in collateral requirements related to the business or credit cycle at the national level. We include seven year dummies, treating 2007 as the reference year. Bank-type fixed effects control for systematic differences in bank propensities to require collateral. In total seven bank-type dummies are included.[14] Provincial fixed effects capture systematic differences in collateralization policies across provinces. We include a total of 31 provincial dummies. Industry dummies control for differences in technology, production and market conditions across different industries, which may account for systematic differences in borrowers' risks. Some strategic or government supported industries might enjoy subsidies or favorable loan contract terms, which should also be accounted for by industry dummies.[15] We group firms into 52 different industries, following the industry classification of Wind Finance Co., Ltd.

2.1.2. Informational transparency of borrowers and collateral incidence

A more precise identification of informational rent extraction is achieved by investigating if the probability of rent extraction by inside banks through collateral varies according to the level of information asymmetries existing among inside and outside lenders. Charging informational rents should be more difficult from transparent firms, since information about these firms is more widely distributed among all lenders. Some intrinsic firm characteristics, such as size or age, are traditionally used as proxies for transparency (Jimenez et al., 2009; Ono and Uesugi, 2009). Specifically, we test the following specification:

$$\mathrm{P(Collateral_{il})} = \mathrm{F}\big(\beta_0 + \beta_1 \mathrm{Sizeconcen_{il}} + \beta_2 \mathrm{ACR4_{il}} + \beta_3 \mathrm{Sizeconcen_{il}} * \mathrm{Infor_{il}} + \beta_4 \mathrm{ACR4_{il}} * \mathrm{Infor_{il}} + + \omega \mathrm{Infor_{il}} + \sum_{j=1} \sigma_j \mathrm{Relcontrols_{il}} + \rho \mathrm{IPO_{il}} + \sum_{j=1} \varphi_j \mathrm{FC_{il}} + \sum_{j=1} \theta_j \mathrm{LC_{il}} + \sum_{j=1} \gamma_j \mathrm{MC_{il}} + \sum_{j=1} \delta_j \mathrm{RC_{il}} + \sum_{j=1} \alpha_j \mathrm{FE_{il}}\big) \quad (2)$$

[14] The different bank-types in our sample are: state-owned banks, joint-stock banks, city commercial banks, rural commercial (co-operative) banks, policy banks, trust and investment companies, foreign banks, the postal savings bank and other financial institutions. Loans from the postal savings bank, represented by only three observations, are all collateralized and therefore excluded from our analysis.

[15] The Chinese State Department announced in October 2010 a list of industries that would receive preferential State support, including, for instance, national defense, emergency preserving, environmental and biotechnology related industries. See the following link (in Chinese) for a list of State supported industries: http://www.gov.cn/zwgk/2010-10/18/content_1724848.htm.

where an informational transparency dummy $Infor_{il}$ is interacted with the relationship lending and market structure variables ($Sizeconcen_{il}$ and $ACR4_{il}$, respectively). We use several alternative variables for $Infor_{il}$: whether the borrower is listed at the main board of the stock exchange ($Listmain_{il}$); whether the borrower is a state-owned firm (FT_{il}); and whether a firm's total assets are above the provincial median ($Medianta_{il}$). $Listmain_{il}$ 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). Firms listed at the latter two boards are typically smaller or high-tech firms, which should be more informational opaque. Firm ownership FT_{il} as a proxy for information transparency in the particular case of China deserves further discussion. Since nearly all banks in China are fully 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 in the literature, with smaller firms considered to be more informational opaque (e.g. Ortiz-Molina and Penas, 2008). We define a dummy $Medianta_{il}$ that equals one if the firm's total assets are above the provincial median, and zero otherwise.

If $\beta_1 > 0$ and $\beta_3 < 0$, or respectively $\beta_2 > 0$ and $\beta_4 < 0$, it would lend 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.

2.1.3. Stock market information spillovers

However, since the informational transparency proxies that we introduced in the previous section are also likely to be 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 and older firms are less likely to face financial stress when compared with smaller and younger firms, these firms have less incentives to pledge collateral to relationship lenders in exchange of a possible future rescue, leading to a smaller impact of relationship intensity on collateral incidence of the former relative to the latter firms. The implicit guarantee enjoyed by state owned firms may render collateral irrelevant in exchange of rescuing from relationship lender. Similarly, as larger and older firms or state owned firms may have greater bargaining power, market structure could affect their collateral pledging less than that of smaller and younger firms.

Thus, we need to apply an exogenous informational equalization shock in order to be able to identify informational rent extraction. An identification strategy can be derived based on the observation that the "hold-up" of borrowers depends on the information asymmetries existing among inside and outside lenders, while informational differences do not play a similar role in the competing theories. The extraction of informational rents by inside banks will be more likely before the informational equalization shock and less likely after, when the informational monopolies of inside banks are reduced and adverse selection problems facing outside banks are alleviated. The existing literature provides several candidates for

such a shock.[16] Following Schenone (2010), we employ the initial public equity offering (IPOs) of the borrowing firm as an information releasing shock that equalizes the distribution of information between inside and outside banks, which reduces the likelihood of rent extraction by the former.

Hence, an important assumption that we make is that a firm's equity IPO reduces information asymmetries between banks, i.e. stock exchange listings provide additional information about firms to all competing lenders. As a next step, we test the validity of this assumption. Validating the information releasing role of the stock market is particularly important for China, given the alleged poor infrastructure and reputational weakness of Chinese stock markets. We employ two measures of information production by stock markets (*StockInfor*$_{il}$): financial analysts' coverage (*Numalst*$_{il}$) and the percentage of shares held by institutional investors (*Instishare*$_{il}$). These measures have the advantage over traditional measures such as firm size or age that firms generally obtain external financial analysts coverage and institutional ownership only after listing. Therefore, they can serve as proxies for stock market information production. Firms followed by more analysts or with a higher percentage of institutional ownership are expected to more informational transparent to all banks. In this setting, if the stock market does not produce extra information or if banks do not take into account this extra information, the variables measuring stock market information production should have no impact on collateral incidence.

To conclude, we estimate the following equation:

$$\begin{aligned} \mathrm{P}(\mathrm{Collateral}_{\mathrm{il}}) = \mathrm{F}(\beta_0 + \beta_1 \mathrm{Sizeconcen}_{\mathrm{il}} + \beta_2 \mathrm{ACR4}_{\mathrm{il}} + \beta_3 \mathrm{Sizeconcen}_{\mathrm{il}} * \mathrm{StockInfor}_{\mathrm{il}} \\ + \beta_4 \mathrm{ACR4}_{\mathrm{il}} * \mathrm{StockInfor}_{\mathrm{il}} + \\ \omega \mathrm{StockInfor}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \sigma_{\mathrm{j}} \mathrm{Relcontrols}_{\mathrm{il}} + \rho \mathrm{IPO}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \varphi_{\mathrm{j}} \mathrm{FC}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \theta_{\mathrm{j}} \mathrm{LC}_{\mathrm{il}} + \\ \sum_{\mathrm{j}=1} \gamma_{\mathrm{j}} \mathrm{MC}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \delta_{\mathrm{j}} \mathrm{RC}_{\mathrm{il}} + \sum_{\mathrm{j}=1} \alpha_{\mathrm{j}} \mathrm{FE}_{\mathrm{il}}) \end{aligned} \quad (3)$$

Negative values for the coefficients β_3 and β_4 of the interaction terms would suggest that inside banks' ability to charge informational rents through relationship lending and concentrated markets (conditional on positive values for β_1 and β_2) is reduced when more information has become available.

[16] Marquez (2002) suggests that in markets with a high turn-over of borrowers, the information advantage of any inside bank is eroded, because all banks are equally uninformed. Padilla and Pagano (2000) propose the establishment of a credit registry that facilitates the information sharing among banks. However, both identification strategies are difficult to apply to Chinese lending markets. In particular, it is not easy to find sufficient lending data for a sector where the turnover of borrowers significantly increases after a certain event. A credit registry system could be an alternative. However, as our sample starts in 2007 and the credit registry system in China was introduced in 2005, it does not constitute an exogenous shock for our sample. Moreover, how effective the Chinese credit registry system is in sharing borrower information is still an open question. The credit registry system also has the shortcoming that it does not report firm characteristics and detailed historical loan contract information, which are central to our analysis. Another advantage of IPOs is that the quality of firm financial data is subject to the scrutiny of the IPO supervising China Securities Regulatory Commission (CSRC), while the quality of the data reported in the credit registry system is not guaranteed.

2.1.4. Equity IPOs as strategy to identify informational rent extraction

Subsequently, we use 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 avoid that any inside bank obtains or maintains an informational monopoly position. Furthermore, a secondary effect might be at work which can reinforce 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 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. When borrowing firms lack a credible channel for disseminating information, such as before an IPO, concentrated markets allow a few inside banks to establish informational advantages and facilitate informational rent extraction. After an IPO, information that previously was concentrated at a small group of inside banks is made public also to outside banks through regularly published financial statements, public auditing, financial analysts' research and movements in stock prices. Hence, information asymmetries among banks are greatly reduced. This dissemination of information due to the public listing of a firm in turn erodes the possibility of informational rent extraction due to market concentration.

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 modification 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 equalization 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 the interaction terms of the relationship intensity and market structure variables, respectively, with IPOs in *Equation (1)*, which yields *Equation (4)*:

$$\begin{aligned} \mathrm{P}(\mathrm{Collateral}_{il}) = \mathrm{F}(&\beta_0 + \beta_1 \mathrm{Sizeconcen}_{il} + \beta_2 \mathrm{ACR4}_{il} + \beta_3 \mathrm{Sizeconcen}_{il} * \mathrm{IPO}_{il} + \beta_4 \mathrm{ACR4}_{il} * \mathrm{IPO}_{il} \\ &+ \\ &\textstyle\sum_{j=1} \sigma_j \mathrm{Relcontrols}_{il} + \sum_{j=1} \mu_j \mathrm{Relcontrols}_{il} * \mathrm{IPO}_{il} + \rho \mathrm{IPO}_{il} + \sum_{j=1} \varphi_j \mathrm{FC}_{il} + \sum_{j=1} \theta_j \mathrm{LC}_{il} + \\ &\textstyle\sum_{j=1} \gamma_j \mathrm{MC}_{il} + \sum_{j=1} \delta_j \mathrm{RC}_{il} + \sum_{j=1} \alpha_j \mathrm{FE}_{il}) \end{aligned} \quad (4)$$

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, such as discussed in Section 1. Further, 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 the IPO.

Employing IPOs as an identification strategy to test for the existence of informational rents has some unique advantages in the context of Chinese banking. Firstly, IPOs in China can be considered exogenous to loans. 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 (CSRC), which is unpredictable and entirely exogenous to both banks and firms. Furthermore, the IPO process in China usually takes years, and during our sample period multiple unexpected suspensions of IPOs occurred.[17] All these features make the exact *timing* of IPOs in China extremely difficult, suggesting that adjustments of loan contract terms prior to an IPO are hardly economically viable. Secondly, equity IPOs are strictly underwritten by security firms instead of commercial banks in China. This alleviates the concern that relationship banks may promise favorable loan contract terms to their clients in exchange for underwriting their IPO.

2.1.5. Informational rent extraction and firm risk

Finally, we investigate whether informational rent extraction is linked to firm risk. Rajan (1992) suggested 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 is equalized among inside and outside banks, informational rents will decline for safer firms but not for risky ones. We test this hypothesis by comparing the impact of informational rent variables on collateral incidence before and after their IPO, and how this impact varies with firm risk.

The riskiness of firms is usually proxied by their credit rating (e.g. Hale and Santos, 2009). However, very few firms are rated before their stock market listing, or even before their first bond IPO. Instead, we propose another measure for firm risk: whether the first IPO application of a firm was rejected by the China Securities Regulatory Commission (CSRC) or not. A firm can be rejected or suspended for IPO evaluation 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.[18] In a way, this measure is similar to a credit rating, but now the firm is rated by a government body instead of private sector rating companies. Comparing the informational rents charged from the firms whose IPO application was once rejected with those approved in their first application allows us to identify if these rents are more likely to be extracted from riskier firms (see also Rajan, 1992; Hale and Santos, 2009).

To investigate this, we expand our baseline *Equation (4)* with an additional dummy variable $Multiapp_{il}$ that takes the value one if firm i applied for its IPO multiple times (before eventually being listed), and equals zero if the IPO was

[17] The unexpected suspensions of IPO applications were Sept 2004-Feb 2005, June 2005-June 2006, Sept 2008- June 2009, Oct 2012-Jan 2014, and Feb 2014-June 2014.

[18] The political capital owned by applicants could also affect IPO approval (see e.g. Liu et al., 2013). Nevertheless, banks may consider firms with less political capital as risky ones.

approved the first time. To test if informational rents vary with firm risk, we introduce three-way interaction terms between our informational rent variables (*Sizeconcen*$_{il}$ and *ACR4*$_{il}$), *IPO*$_{il}$ and *Multiapp*$_{il}$.

2.2. Data

We manually collect unique *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). Listed firms were required by the CSRC to disclose their most important loans in the appendices of Annual and Semi-annual Reports after 2007.[19] We concentrate on companies listed at the Shenzhen Stock Exchange (SZSE), as firms listed at this exchange are more diverse in terms of firm size when compared with those listed at the Shanghai Stock Exchange. 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 four banks per firm), including almost all types of Chinese banks. Furthermore, many listed firms provide loan and financial data both before and after their IPO, which allows us to assess adjustments in collateral incidence around the moment of the IPO rather precisely. This feature of the data also alleviates the concern that changes in the pattern of collateral incidence around IPO events are driven by changes in firm characteristics.

Our dataset consists of 10,654 loans made to 676 firms listed at the SZSE between 2007 and 2013.[20] 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 all reduces our database to 9,288 loans provided to 649 listed non-financial firms.

Information on the amount and type of collateral is not available; hence, we focus on the incidence of collateral instead ("yes" or "no"). Summary statistics of our binary dependent variable *Collateral*$_{il}$ and for the explanatory variables are provided in Table I. 66% of the loans in our database are collateralized (Panel C), 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).

[19] Some firms report almost all their loans for each fiscal year while others report the important loans. The important loans are usually large loans relative to firm size. Having a sample composed of large loans bias against of finding informational rent, because potential lenders may compete more aggressively on large loans which reduces the incumbent bank's informational advantage.

[20] Unfortunately, listed firms do not report if 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.

Our main relationship variable $Sizeconcen_{il}$ has an average value of 0.33 (Panel D), suggesting that on average around one third of the amount of loans is obtained from the current lender. Regarding other relationship controls, the average for $Numlender_{il}$ shows that an average firm in our sample borrowed from four different banks, with a relatively high standard deviation of three banks. Moreover, the average value for $Switch_{il}$ is 0.4, indicating that for somewhat less than half of the loans, firms switched banks.

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 (Table I, Panel A). The most concentrated market is Tibet province (with a concentration ratio of 97%), while the least concentrated market is Shanghai province (concentration ratio of 35%). Data are obtained from the People's Bank of China. For current loan l, we use the concentration ratio measured one semi-accounting year prior to this loan.

The summary statistics for IPO_{il} show that 83% of the loans in our sample were issued after an IPO (Table I, Panel B). Among the 649 firms in our sample, 111 firms reported at least one loan before their IPO and at least one after; in total these firms had 2,181 loans, representing 23% of all loans. The rest of the 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 take up 40% of all loans. We obtain all firm characteristics (except Age_{il}) from the semi-annual financial reports that were published the closest to the moment before the loan was originated.[21] For instance, if a loan was granted in the first half of an accounting year, for example in March 2008, then the corresponding firm characteristics are obtained from the financial report ending December 31st, 2007. For a loan originated during the second half of an accounting year, for example in July 2008, the firm characteristics are obtained from the report ending June 30st, 2008. This procedure ensures that in our estimations, banks use the most recent publicly available accounting information at the time of issuing the loan.

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 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% (Table I, Panel C).

For the monetary policy controls, we match the month when the loan was originated with the corresponding reserve requirements ratio and repo rate of that month. The regional macroeconomic variables have a yearly frequency. For loan l, we use the respective regional macroeconomic variables one semi-accounting year before loan l was originated. All these data come from the CEIC database. Of the other controls, we provide further detail only for the variable that we used to investigate rent extraction and firm risk, i.e. $Multiapp_i$ that measures if the firm is rejected in the IPO application. In our sample, most of the firms received approval at their first IPO application; 40 firms, or around 7% of all firms, were rejected or suspended for IPO evaluation when they applied for the first time (but were

[21] Listed firms are required to provide annual reports and semiannual reports by the end of the year (December 31th) and in the middle of the year (June 30th).

eventually listed, after multiple applications). Definitions and summary statistics of instrumental variables and additional variables are reported in Table I, panel G, E.

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

Table I: Continued

Variable	Definition	N	Mean	S.D	Min	Max
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
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
Instshare	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
Wedge	The difference between the control rights and cash-flow rights of the ultimate owner of the firm. Measured at one semi-accounting year before loan origination, in percentage.	7699	6.32	8.98	0	39.43
Cashflowrights	The cash-flow rights of the ultimate owner of the firm. Measured at one semi-accounting year before loan origination, in percentage.	7699	31.49	18.65	0	89.40
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

3. Main results

3.1. Univariate tests

In this section, we compare if the mean values of the key variables differ across relationship intensity, market structure and before or after IPOs. Results are reported in Table II. Panel A compares several key explanatory variables for relationship loans ($Sizeconcen_{il}$>=median) and non-relationship loans ($Sizeconcen_{il}$<median); Panel B reports the mean differences of key explanatory variables for concentrated markets ($ACR4_{il}$>=median) and markets with low concentration ratios ($ACR4_{il}$<median); and lastly Panel C compares the key variables before and after IPOs.

Relationship loans on average enjoy better loan terms such as longer maturity and lower lending spreads. At the same time, these loans are smaller; on average, collateral requirements do not differ significantly between relationship and non-relationship loans.

Collateral requirements are significantly more severe in concentrated markets than in markets with low concentration ratios. Loan maturity does not differ across markets, while loan size and the average lending spread are significantly larger in lowly concentrated markets. The latter result is somewhat counter-intuitive, but may be explained by the fact that in lending markets characterized by low concentration ratios usually many smaller banks are active. These banks are generally specialized in lending to small and medium-sized firms. Taking the simple average of lending spreads without taking into account risk premia associated with this lending could drive this result. 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, for loans originated after the IPO, the corresponding average characteristics of the borrowing firms also differ significantly from those that obtained loans before the IPO. Compared to pre-IPO loans, firms that borrowed after the IPOs are less liquid and less profitable, but the leverage ratio of borrowing firms does not differ before and after the IPO.

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.

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* might be endogenous, we follow Berger and Udell (1995) and estimate the model with and without these terms (Columns (1) and (2), respectively). We shall conduct additional robustness tests for endogeneity issues in Section 5.3.

Our results show that relationship intensity is positively related to the incidence of collateral and highly significant. The marginal effects show that 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 Section 2.1 (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), Lehmann and Neuberger (2001) and Ono and Uesugi (2009).

Market structure, measured as the concentration ratio *ACR4*, is positive and highly significant at 1% 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 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%.[22] 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 the 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 the lending rate.

Before moving forward, we discuss briefly the impact of the other determinants on collateral incidence, which has merit in itself, as the existing literature on Chinese lending markets has investigated this issue only using firm-year data (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.[23]

Firm ownership in China is considered as a particularly important risk factor by banks. Previous empirical studies demonstrated that private firms in China have been financially discriminated in a state-dominant banking system (Cull and Xu, 2003; Allen et al., 2005). Our results complement this literature by showing that privately owned firms are also more likely to pledge collateral. This result may be explained by the implicit guarantee from the State, which establishes for state-owned firms an alternative risk-mitigating mechanism to collateral. The marginal effect of firm ownership suggests that private firms in China have on average a 16.7% higher probability of pledging collateral than state-owned firms, which is the largest marginal effect that we find for all control variables. Since the private firms in our sample are relatively large and reputable, this degree of financial discrimination in terms of collateral suggests that most likely smaller and less renowned private firms in China suffer even more.

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

[23] See for instance Boot et al. (1991), Dennis et al. (2000) and Bharath et al. (2011) for similar results.

To summarize, our results for firm characteristics largely confirm the "observed-risk" hypothesis (Boot et al., 1991; Boot and Thakor, 1994) that collateral incidence is associated with risky borrowers, and probably serves as a tool to solve moral hazard problems.[24] These findings, however, are not consistent with the "signaling" model (Chan and Kanatas, 1985; Bester, 1985 and 1987; Besanko and Thakor, 1987), which predict that low risk borrowers are more likely to pledge collateral in order to signal their credit quality.

Other loan contract terms seem to 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. Myers, 1977; Berlin and Mester, 1992; Flannery, 1986; Barclay et al., 1995). Thus, shorter loan maturity and collateral seem to be alternative mechanisms to control for borrowers' risk.[25] 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%.[26] 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 limited impact on the incidence of collateral, with only the *7-day Repo* rate being positively related to collateral at the 10% significance level.[27] Regional macroeconomic variables (*CPI*, *NPLratio* and *Realgdpindex*) generally do not affect collateral decisions. It is likely that the impact of business cycle changes 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.[28] As a further robustness check, we include

[24] Similar findings to ours are reported in previous studies for both developed and developing countries (Berger and Udell, 1990 and 1995; Dennis et al., 2000; Menkhoff et al., 2006; Brick and Palia, 2007).

[25] See Ortiz-Molina and Penas (2008), Leeth and Scott (1989), Degryse and Van Cayseele (2000) and Dennis et al. (2000) for similar findings.

[26] 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 Steijvers and Voordeckers (2009) and Boot et al. (1991).

[27] 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 shall leave to future research.

[28] The results for industry, province, bank-type and loan-year dummies are not reported to save space. They are available upon request.

regional legal and institutional variables.[29] Our results do not materially change when these additional controls are added.

3.2.2. Does firm informational transparency affect collateral incidence?

Next, we investigate whether collateral incidence is related to the informational transparency of firms. To this extent, we estimate *Equation (2)* in Section 2.1.2. The key variables are three informational transparency proxies ($Infor_{il}$) indicating whether a borrowing firm is listed at the main board of the Shenzhen Stock Exchange (SZSE), $Listmain_{il}$;[30] whether the borrower is a state-owned firm (FT_{il}); and whether the borrower is large ($Medianta_{il}$). Results are reported in Table III, Panel B.[31]

We first explain the results for the informational opaque firms. Our results indicate that firms which are not listed at the main board, privately owned or small, are more likely to pledge collateral when relationship intensity increases, as suggested by the significantly positive coefficients of $Sizeconcen_{il}$ in all specifications. For informational 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 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. These results confirm that firms borrowing in more concentrated markets are more likely to pledge collateral, and this effect is stronger for informational opaque firms.

The above results are in line with the prediction that inside banks charge informational rents through collateral. However, as these information transparency proxies are also likely to be correlated with firms' probability of obtaining re-financing or bargaining power over lenders, these results are also consistent with the "soft budget constraint" and "market power" explanations. For example, the implicit guarantee from the State implies that (inside) collateral is not an essential

[29] 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.

[30] 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.

[31] Removing Maturity and Spread in Panel B does not affect our results. Results are available upon request.

Table III: Collateral determinants and borrower information transparency

Panel A shows the results for the estimation of *Equation (1)*, where borrower-lender relationship (*Relationship*) is proxied by *Sizeconcen*, such as defined in Table I. 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). 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. 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			Panel B: *Borrower information transparency*		
	With contract terms	Without contract terms	M.E of model (1) (%)	Board of listing	Ownership	Firm size
VARIABLES	(1)	(2)		(3)	(4)	(5)
Sizeconcen	0.153**	0.170**	1.40	0.231***	0.256***	0.287***
	(0.068)	(0.068)		(0.085)	(0.082)	(0.076)
ACR4	2.685***	2.623***	4.45	3.826***	3.463***	3.482***
	(0.805)	(0.802)		(0.895)	(0.858)	(0.832)
Listmain*Sizeconcen				-0.129		
				(0.098)		
FT*Sizeconcen					-0.203**	
					(0.098)	
Medianta*Sizeconcen						-0.390***
						(0.102)
Listmain*ACR4				-1.664***		
				(0.616)		
FT*ACR4					-1.603***	
					(0.619)	
Medianta*ACR4						-2.051***
						(0.571)
Listmain				0.705**		
				(0.346)		
Medianta						1.334***
						(0.316)
FT	-0.606***	-0.594***	-16.7	-0.565***	0.335	-0.618***
	(0.047)	(0.046)		(0.048)	(0.340)	(0.047)
First	0.036	0.049	0.94	0.048	0.044	0.019
	(0.056)	(0.055)		(0.056)	(0.056)	(0.056)
Switch	-0.028	-0.064	-0.75	-0.033	-0.028	-0.023
	(0.039)	(0.039)		(0.040)	(0.039)	(0.039)
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***
	(0.007)	(0.007)		(0.007)	(0.007)	(0.008)
Liquidity	-0.458***	-0.545***	-2.76	-0.504***	-0.447***	-0.375**
	(0.155)	(0.153)		(0.156)	(0.155)	(0.155)

Table III: Continued

Size	-0.221***	-0.215***	-7.29	-0.191***	-0.222***	-0.233***
	(0.027)	(0.027)		(0.028)	(0.027)	(0.030)
Leverage	0.941***	1.049***	4.53	1.040***	0.926***	0.951***
	(0.127)	(0.126)		(0.129)	(0.127)	(0.127)
ROA	-1.134***	-1.084***	-2.22	-1.124***	-1.102***	-1.160***
	(0.277)	(0.282)		(0.279)	(0.278)	(0.276)
Age	-0.415***	-0.432***	-4.50	-0.331***	-0.419***	-0.409***
	(0.058)	(0.057)		(0.060)	(0.058)	(0.058)
Tangibility	-0.852***	-0.891***	-4.43	-0.893***	-0.855***	-0.782***
	(0.179)	(0.178)		(0.180)	(0.179)	(0.179)
Maturity	0.169***		3.39	0.169***	0.169***	0.171***
	(0.028)			(0.028)	(0.028)	(0.028)
Spread	0.031*		1.00	0.036**	0.031*	0.035**
	(0.017)			(0.017)	(0.017)	(0.017)
Loansize	-0.089***	-0.070***	-3.37	-0.090***	-0.090***	-0.090***
	(0.020)	(0.020)		(0.020)	(0.020)	(0.020)
Loanconcen	1.830***	1.921***	3.37	1.956***	1.804***	1.866***
	(0.413)	(0.408)		(0.410)	(0.414)	(0.415)
RRR	-0.071	-0.021	-0.05	0.050	-0.202	-0.188
	(2.902)	(2.884)		(2.909)	(2.904)	(2.907)
Repo	0.048*	0.045*	1.51	0.044	0.048*	0.050*
	(0.027)	(0.027)		(0.027)	(0.027)	(0.027)
CPI	1.475	2.003	1.04	1.241	1.320	1.518
	(1.510)	(1.501)		(1.514)	(1.513)	(1.513)
NPLratio	-0.535	-0.647	-0.42	-0.305	-0.526	-0.685
	(1.135)	(1.132)		(1.137)	(1.135)	(1.140)
Realgdpindex	1.097	1.548	1.00	0.763	0.787	0.975
	(1.435)	(1.429)		(1.441)	(1.442)	(1.439)
Constant	-0.566	-0.644		-1.577	-0.850	-1.123
	(1.874)	(1.869)		(1.888)	(1.879)	(1.884)
Observations	8,741	8,753		8,741	8,741	8,741
Fixed effects dummies	Industry, Province, Bank Type, Time					
Pseudo R2	0.287	0.283		0.289	0.288	0.290
H_0:Sizeconcen+*Infor*Sizeco*ncen=0				0.102	0.052	-0.103
H_0: *ACR4+Infor*ACR4*=0				2.162***	1.860**	1.431

precondition for relationship lenders to re-finance distressed state-owned firms, which can lead to a lower impact of relationship intensity on collateral incidence for these firms. State-owned firms are also likely to have stronger bargaining power over banks, therefore reducing the impact of market structure on the pledging of collateral. Similar arguments apply when firm size is used as an information transparency proxy. These arguments predict that the coefficients of the interaction terms should be negative, which can be a result independently from the informational rent extraction hypothesis. To better test this hypothesis, in the next sections we use equity IPOs as exogenous informational equalization shocks that

change the informational transparency of firms, and therefore reduce the capacity of inside banks to extract informational rents.

3.2.3. Does the stock market produce information?

Our use of equity IPOs as the identification strategy lies crucially on the assumption that the stock market provides additional information about firms to all competing banks. This information production of the stock market and the subsequent information spill-over to outside lenders should lower information asymmetries among banks, which reduces the likelihood of rent extraction by inside banks. Hence, in this section, first we want to establish whether the Chinese stock market produces additional information that affects the collateral requirements of inside banks. We estimate *Equation (3)* (Section 2.1.3), concentrating on the results for the two proxies for information production: financial analysts' coverage ($Numalst_{il}$) and institutional ownership ($Instishare_{il}$). Definitions and summary statistics of these variables are reported in Table I, while the results are shown in Table IV. Second, we investigate if information spill-overs from stock market listings generate a boundary transparency level beyond which inside and outside banks are equally informed, and thus inside banks can no longer extract informational rents. As the focus in this section is on information production role of the stock market, we restrict the sample exclusively to post-IPO loans.

We show in Columns (1) and (3) of Table IV that the coefficients of both information production variables are significantly negative, indicating that banks reduce collateral requirements when more information is produced by the stock market. This result confirms that stock markets do produce extra information and that banks incorporate this information in their collateral decisions. Columns (2) and (4) show that all interaction terms are significantly negative. The magnitude of the coefficients suggests that inside banks' ability to charge informational rents depends on the level of information production by the stock market. Specifically, a borrower which is followed by less than 11 analysts (65th percentile) is expected to pay more collateral when its relationship intensity increases, while this effect become statistically indistinguishable from zero above this threshold. Similarly, borrowers followed by less than 22 analysts (88th percentile) are more likely to pledge collateral when market concentration increases, while this effect vanishes when more analysts follow the firm.

We obtain similar results when share ownership of institutional investors serves as a measure of information production. Collateral incidence for firms with institutional ownership below 70% (96th percentile) increases with the degree of market concentration. This result suggests that concentrated markets allow inside banks to charge rents over the vast majority of firms. In terms of relationship lending, we find that collateral incidence increases with relationship lending for firms with a share of institutional ownership below 20% (55th percentile).

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 in Columns (5) and (6) of Table IV by incorporating corporate governance variables that directly affect firms' tunneling incentives: the "control and cash flow rights" wedge (*Wedge*), and cash-flow rights (*Cashflowrights*). Definitions of these variables are in Table I. Our previous results remain intact.

Table IV: Stock market information production and collateral

This table reports the results for the estimation of *Equation (3)* on stock market information production and how the impact of inside banks' ability varies according to post-IPO information production. Control variables are the same as in Table III, Column (1). The sample is restricted to post-IPO loans. Column (1) and (2) use the number of analysts (*Numalst*) as measure for stock market information production, while Column (3)-(6) employ shareholding (ownership) by institutional investors (*Instishare*). Column (5) and (6) expand Column (4) by further controlling for corporate governance variables (*Wedge* and *Cashflowrights*). 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)	(5)	(6)
Sizeconcen	0.107	0.209**	0.087	0.277***	0.078	0.268***
	(0.073)	(0.088)	(0.073)	(0.097)	(0.073)	(0.097)
ACR4	3.796***	4.912***	3.681***	4.897***	3.623***	4.782***
	(0.864)	(0.901)	(0.862)	(0.924)	(0.862)	(0.924)
Numalst	-0.010***	0.074***				
	(0.002)	(0.017)				
Sizeconcen*Numalst		-0.010**				
		(0.005)				
ACR4*Numalst		-0.149***				
		(0.032)				
Instishare			-0.330***	2.574***	-0.300***	2.480***
			(0.096)	(0.722)	(0.096)	(0.723)
Sizeconcen*Instishare				-0.770***		-0.763***
				(0.240)		(0.241)
ACR4*Instishare				-4.924***		-4.701***
				(1.318)		(1.320)
Wedge					-0.002	-0.002
					(0.002)	(0.002)
Cashflowrights					0.001	0.001
					(0.001)	(0.001)
Constant	-6.203	-7.478	-6.283	-6.924	-6.514	-7.099
	(107.011)	(106.776)	(106.878)	(106.273)	(106.433)	(105.908)
Observations	7,620	7,620	7,620	7,620	7,600	7,600
Controls: firm characteristics, monetary policy and regional macro variables, loan characteristics; industry, province, bank type and time fixed effects						
Pseudo R2	0.289	0.291	0.288	0.291	0.289	0.291

3.2.4. Do equity IPOs reduce informational rents?

In this section, we provide a direct test of informational rent extraction, i.e. we compare the impact of $Sizeconcen_{il}$ and $ACR4_{il}$ on collateral incidence before and after equity IPO. Estimations are based on *Equation (4)*. The set of $Relcontrols_{il}$ include $First_{il}$, $Switch_{il}$, and $Numlender_{il}$. In all specifications, the interaction terms of $First_{il}$* IPO_{il}, $Switch_{il}$* IPO_{il} and $Numlender_{il}$* IPO_{il} are included to control for the

possible heterogeneous impact of these factors on collateral pledging before and after the IPO.[32]

Results are reported in Table V. 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 our main indicator for relationship intensity $Sizeconcen_{il}$ 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 is significantly negative across all specifications. As the results of these three specifications are quantitatively similar, we explain in more detail only the results presented in Column (3), 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 caused by a reduction in information asymmetries between inside and outside banks after the IPO, which makes it more difficult to establish "hold-ups" through relationship lending. If one assumes that the IPO eliminates completely informational asymmetries among lenders, the "informational rent" theory explains roughly 75% ((4.78%-1.17%)/4.78%) of the impact of relationship lending on collateral. This result confirms our Hypothesis H.3 that the "hold-up" problem resulting from relationship lending is less likely to occur if all banks are relatively symmetrically informed (see Section 2.1.4).

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 compared to loans borrowed in markets with much lower degrees of concentration. 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% before the IPO, while after the IPO 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 after the IPO. This result confirms Hypothesis H.4 (Section 2.1.4).

[32] A full-fledged model with IPO_{il} dummies interacting with all covariates (except monetary policy and regional macroeconomic variables and fixed effects dummies) is estimated as a further robustness check. Results are quantitatively similar and are not reported for space considerations. Results are available upon request.

Finally, looking at the quantitative significance of the results for market structure, roughly half ((8.51%-4.15%)/8.51%) of the positive impact of market concentration on collateral is explained by informational rent extraction. This result lends some support to the view that information asymmetries are not the only channel that may lead to higher collateral incidence in concentrated markets. The "market power channel", which we discussed in Section 1, suggests that monopolistic or oligopolistic banks can extract rents by using their market power, increasing collateral requirements even in environments 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 will improve their access to capital markets or increase their attractiveness as a client for other lenders. This would reduce the positive impact of bank market structure on collateral incidence. We control for possible shifts in borrowing firms' bargaining power by introducing the interaction term $Numlender_{il}*IPO_{il}$. It is expected that firms that can borrow from more different lenders may benefit from higher intra-bank competition, 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 the 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, suggesting that changes in bargaining power around the moment of the IPO are unlikely to drive our results.

Next, we investigate the other control variables. Firstil is significantly positive before the IPO, indicating that borrowing for the first time from a certain lender before the IPO is associated with a higher likelihood of collateral pledging. After listing, 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 informational equalization role of IPOs. 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 of other control variables are similar to those reported in Table III.

To conclude, using IPOs as an informational equalization shock, the results in this section provide evidence of informational rent extraction by informed banks, whether the informational advantage is driven by relationship lending or concentrated markets.

Table V: Identify informational rents through IPOs

This table reports estimates based on various versions of *Equation (4)*. 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 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)	
FT	-0.607***	-0.608***	-0.612***	-0.599***	-16.78
	(0.047)	(0.047)	(0.047)	(0.046)	
Liquidity	-0.493***	-0.471***	-0.472***	-0.559***	-2.84
	(0.155)	(0.155)	(0.155)	(0.154)	
Size	-0.220***	-0.222***	-0.220***	-0.215***	-7.24
	(0.027)	(0.027)	(0.027)	(0.027)	
Leverage	0.940***	0.948***	0.949***	1.056***	4.56
	(0.127)	(0.127)	(0.127)	(0.126)	
ROA	-1.172***	-1.144***	-1.157***	-1.109***	-2.26
	(0.276)	(0.279)	(0.279)	(0.283)	
Age	-0.413***	-0.417***	-0.417***	-0.434***	-4.50
	(0.058)	(0.058)	(0.058)	(0.058)	
Tangibility	-0.881***	-0.879***	-0.885***	-0.924***	-4.60
	(0.179)	(0.179)	(0.179)	(0.178)	

Table V: Continued

VARIABLES	(1)	(2)	(3)	(4)	M.E. of Model (3)
Maturity	0.171***	0.170***	0.170***		3.40
	(0.028)	(0.028)	(0.028)		
Spread	0.034**	0.032*	0.033*		1.04
	(0.017)	(0.017)	(0.017)		
Loansize	-0.091***	-0.092***	-0.092***	-0.073***	-3.47
	(0.020)	(0.020)	(0.020)	(0.020)	
Loanconcen	1.820***	1.815***	1.819***	1.912***	3.34
	(0.413)	(0.413)	(0.413)	(0.408)	
RRR	-0.051	0.095	0.062	0.098	0.04
	(2.908)	(2.908)	(2.908)	(2.889)	
Repo	0.047*	0.045*	0.046*	0.042	1.43
	(0.027)	(0.027)	(0.027)	(0.027)	
CPI	1.583	1.616	1.610	2.150	1.13
	(1.513)	(1.514)	(1.514)	(1.505)	
NPLratio	-0.576	-0.586	-0.597	-0.713	-0.46
	(1.136)	(1.135)	(1.135)	(1.132)	
Realgdpindex	1.233	1.180	1.192	1.651	0.97
	(1.438)	(1.439)	(1.439)	(1.432)	
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				
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*	

3.2.5. Do informational rents vary with firm risk?

Finally, we report the results of our investigation whether informational rent extraction is linked to firm risk. More specific, we test the hypothesis whether information equalization between inside and outside lenders reduces informational rents for safe firms, but not, or to a lesser extent, for risky firms. To test this, we expand baseline *Equation (4)* with our proxy for firm risk, $Multiapp_{il}$, which takes the value 1 if a firm applies for an IPO more than once (see Section 2.1.5). To test if informational rents vary with firm risk, we introduce the three-way interaction terms between our informational rent variables ($Sizeconcen_{il}$ or $ACR4_{il}$), IPO_{il} and $Multiapp_{il}$. Results are reported in Table VI.

In the first column, we examine the main effect of $Multiapp_{il}$. A firm with multiple applications is 7% more likely to hold collateral than first-time approved firms. This result supports the use of this variable as a measure for 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

Table VI: 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

collateral are all positive both before and after IPOs. However, whether these marginal effects are moderated after IPOs depends on the riskiness of firms. To see this, we calculate the changes in the marginal effects of the informational rent variables after and before IPOs, for both 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 effects 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 the 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 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)). Our results remain the same.

4. Alternative explanations

This section investigates whether alternative theories than informational rent extraction possibly can explain the moderated effect of relationship lending on collateral incidence after a firm's IPO.[33] One possible alternative is the performance of the firm improves significantly after the IPO. This would reduce the need to post collateral from the lender's perspective, as the risk of financial distress is lowered. Another possibility is that relationship dependent and non-dependent firms experience heterogeneous dynamics regarding their creditworthiness around the IPO. More specifically, we want to investigate the possibility that relationship dependent firms become less risky after the IPO, while non-dependent firms become more risky. These scenarios could drive our results as predicted by Boot (2000) and Longhofer and Santos (2000) who suggest that the positive impact of relationship lending is less pronounced for financially sound firms.

To address these concerns, first we investigate if firm performance improves after the IPO (Section 4.1). Then we employ a difference-in-difference test to examine directly if changes in firm-risk proxies around the IPO differ significantly between relationship dependent and non-dependent firms (Section 4.2). To fully remove this concern, as a further robustness test, we employ Propensity Score Matching (e.g. Heckman et al., 1998) to find matching firms that differ only in whether the loan is obtained from a relationship lender or not (Internet Appendix A). We find matching firms within both pre- and post-IPO samples, and compare the collateral incidence between relationship and non-relationship (or transactional) loans within both samples. If relationship banks charge informational rents and if IPOs equalize information among lenders, then the average treatment effect of relationship lending should be positive for pre-IPO loans and be moderated or insignificant for post-IPO loans. In this way, we can discard of the alternative explanation that some unobserved shifts in firm-risk or heterogeneous dynamics of

[33] We can discard rather straightforward 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 Section 1. This interpretation is not able to explain our results, as this incentive will not change after borrowers obtain stock market listings. Hence, the observed significant and negative coefficient of the interaction term $Sizeconcenil*IPO_{il}$ is not supported by this theory.

risk shifting due to the IPO drive our results, because we compare matching firms within both pre- and post-IPO samples.

A final alternative explanation that we explore is that relationship banks reduce their collateral requirements in exchange for corporate bond underwriting business (Section 4.3). This behavior could also moderate the positive effect of Sizeconcen on collateral incidence if many loans are issued after a firm's bond IPO. To isolate this alternative explanation, we re-estimate the baseline model taking into account only loans that were originated before bond IPOs.

4.1. Improvements in firm performance after the equity IPO

Both Boot (2000) and Longhofer and Santos (2000) (see Section 1) predict a weaker positive correlation between relationship lending and collateral incidence for financially sound firms relative to distressed firms. If firms were to improve their performance substantially after their IPO, our results could also be in line with this alternative explanation. However, various studies have shown that the operating performance of listed Chinese firms drops markedly after their IPOs. For example, Allen et al. (2014) compare the operating performance of listed and non-listed firms in China for the years around the IPO and find that the average return on assets of the former drops significantly from 0.12 to 0.07 within a [-3, 3] years window. This sudden drop is not observed for the latter group of firms over the same time horizon. These authors attribute the deterioration of performance to the extremely strict listing requirements of the CSRC,[34] which induce firms to improve earnings in the years prior to the IPO in order to meet these requirements, adjusting operations to generate short-term profits at the cost of sacrificing long-term growth. This deterioration of operating performance is best illustrated in our sample by observing an astonishing average drop in return on assets by 10% (e.g. from 15% prior to the IPO to 5% after, see Table II).

4.2. Heterogeneous firm-risk dynamics around the equity IPO

Another possibility is that relationship-lending dependent firms improve their financial performance after IPOs, while that of non-dependent firms deteriorates. To address this concern, we directly test whether changes in the key proxies for firm-risk around IPOs vary in different ways, depending on whether the firm relies on relationship lenders or not. In a fashion similar to Presbitero and Zazzaro (2010), we define relationship dependent firms if *Sizeconcen* is above or equal to sample median. We construct difference-in-differences tests for the key financial risk proxies (*ROA, Leverage, Tangibility, Liquidity, Size, Maturity, Spread* and *Loansize*). Specifically, we estimate a linear regression for each of the firm-risk proxies on IPO_{il}, a dummy variable of relationship dependency (equals 1 if $Sizeconcen_{il}$ is above or equal to the sample median, and 0 otherwise) and interaction terms for these two variables. The coefficient of the interaction term and its statistical significance indicate whether relationship dependent and non-dependent firms experience different firm-risk dynamics before and after IPOs. Results are reported in the

[34] 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.

Internet Appendix, Table IA.I. In all these difference-in-difference tests, the interaction terms are statistically insignificant except for *Liquidity*. Hence, we conclude that it is highly unlikely that heterogeneous dynamics of firm-risk around IPOs are driving our results.

In addition, we conduct matched sample analysis within pre- and post-IPO samples and compare the impact of relationship lending intensity on collateral pledging within each subsample. The idea is to compare the collateral incidence of loans of specific firms to "matched" firms that are "identical" in every aspect, except for their relationship intensity. The observed difference in collateral incidence between control and treatment groups would then be a robust effect of relationship intensity. This way we fully remove the possibility that heterogeneous firm-risk dynamics around IPOs could be driving our results. We find that relationship dependent firms are on average 10% to 12% more likely to pledge collateral relative to matched non-dependent firms before the IPO, while the difference between these two groups vanishes after the IPO. Technical details, estimation results and sensitivity tests of propensity score matching are reported in the Internet Appendix, Section A and Tables IA.II-III.

4.3. Corporate bond underwriting and concurrent lending

Our last exploration of alternative explanations lies in the possibility that commercial banks may exchange better loan conditions for corporate bond underwriting business.[35] As most firms have their bond IPO after the equity IPO, and many firms choose their relationship banks as underwriters, our finding of a reduced impact of relationship lending on collateral incidence after the equity IPO could be the result of exchanging better 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 that could drive our results. To address this issue, we construct a sample that only incorporates loans that were granted before the 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. This test validates our findings and shows that they are not driven by concurrent lending and underwriting business related to corporate bond issuance.[36]

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

[36] 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.

5. Further robustness tests

To further test the robustness of our results, we investigate whether our results are sensitive to unobserved risk factors (5.1), sample selection (5.2) and possible endogeneity of loan contract terms (5.3). On the first concern, it is possible that firms which borrow from relationship lenders are riskier than those borrowing from transactional lenders and that our framework has not fully controlled for the unobserved differences in firm-risk. This difference in unobserved firm-risk could be a reason why relationship lenders are more likely to require collateral than other lenders. We address this concern in two ways. First, we re-estimate our baseline model including firm fixed effects that will absorb time-invariant differences in firm-risk among borrowers. Second, to control for unobserved risk factors that determine both bank-firm relationship formation and collateral incidence, we estimate Heckman's 2-stage model to correct for self-selection bias (e.g. Heckman, 1979). On the second concern, we re-estimate the baseline model for different samples to assess whether our results are sensitive to sample selection. Finally, we check whether the endogeneity of loan contract terms affects our results by estimating an instrument variable (IV) Probit model.

Our main results are robust to all these tests. For brevity, we report most of these tests in the Internet Appendix.

5.1. Unobserved risk factors

5.1.1. Firm fixed effects

Including firm fixed effects alleviates the concern that unobserved time-invariant risk factors can affect our results. As the Probit model is not suitable for fixed effects regressions, we resort to the 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 firms' bond IPOs. Some firm characteristics are less precisely estimated when compared to the pooled Probit model, but the results for our key variables, i.e. $Sizeconcen_{il}$, $ACR4_{il}$ and their interaction terms with IPO_{il}, are consistent with the pooled results and are robust for alternative samples.[37]

More specifically, after controlling for firm fixed effects, the impact of relationship intensity on collateral incidence for loans originated after the equity IPO is statistically insignificant across all specifications, as the null hypothesis 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 V), supporting the hypothesis that IPOs as informational equalization shock eliminate rent extraction opportunities. The coefficient of market concentration remains significantly positive, but is moderated for loans originated after IPOs, consistent with our previous findings.

[37] Monetary policy variables and regional macroeconomic variables not included as control variables in this section. Including those variables leads to similar results, which are available upon request.

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. 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)
Fixed effects dummies	Bank Type, Time			
Firm characteristics	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Monetary policy variables	No	No	No	No
Regional macro variables	No	No	No	No
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*

5.1.2. Self-selection of relationship lending

Another source of endogeneity are unobserved factors that affect both the decision to borrow from relationship lenders and the decision to pledge collateral.[38] Our estimates will be inconsistent if these unobserved attributes are ignored. Firm fixed effects regressions alleviate this problem if the unobservable attributes are time invariant. However, if they are time varying, incorporating firm fixed effects will still generate inconsistent estimates. To address these concerns, we use a bivariate Probit model to control for the joint decision of forming bank-firm relationships and pledging collateral. Technical details of this Heckman 2-stage correction model and results are reported in the Internet Appendix, Section B and Table IA.V. The results for the selection equation show (Column (1) and (3)) that 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 ($Loanconcen_{il}$). Firms in provinces with higher average lending rates (*Localavrate*) (see Internet Appendix, Section B for discussion on the validity of this variable as instrumental variable) are also more likely to borrow from relationship lenders. Turning to the outcome equation, the estimates that are adjusted for endogeneity (shown in Columns (2) and (4)) reinforce our baseline results. That is, before the IPO, the likelihood of collateral incidence is higher when the loan is borrowed from relationship lenders, whereas after the IPO the impact of relationship lending on the pledging of collateral is reduced substantially (but remains positive and statistically significant). Results for market structure are also consistent with our previous findings, i.e. the coefficient of the concentration ratio $ACR4_{il}$ is significant and positive, while the coefficient of its interaction term with IPO_{il} is significant and negative. Furthermore, more concentrated markets are again associated with higher collateral incidence even after the equity IPO of borrowing firms, as the null hypothesis H_0: $ACR4_{il}+ACR4_{il}*IPO_{il}=0$ is rejected at the 5% significance level, regardless whether other loan contract terms are included or not.

5.2. Sample selection

We investigate in this section if our results are sensitive to sample selection. First, we focus on a sample of firms that borrowed at least once before the equity IPO and at least once after, which allows us to compare more precisely changes in collateral incidence around IPOs. This selection procedure reduces the size of the sample considerably, with only 111 firms and 2,181 loans remaining. The model specification in this section is similar to *Equation (4)*, but without monetary policy

[38] 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. 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.

variables and regional macro-economic variables.[39] Results are reported in the Internet Appendix, Table IA.VI, Column (1). The coefficients of the key variables, i.e. $Sizeconcen_{il}$, $ACR4_{il}$, $Sizeconcen_{il}$*IPO_{il} and $ACR4_{il}$*IPO_{il}, have the same signs and similar sizes as before.

Next, we restrict ourselves to a sample of loans issued round IPO dates. The underlining assumption is that the effect of IPOs might be short-lived, as discussed in Pagano et al. (1998). This short event window also minimizes the possibility that significant events other than IPOs may affect our results. Specifically, 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). Results are reported in the Internet Appendix, Table IA.VI, Column (2)-Column (4). Our previous results do not materially change for these alternative samples.

Lastly, we investigate if excluding loans issued on a non-commercial basis will change our results. For instance, policy banks in China are specialized in providing government policy related loans. State owned banks might issue loans to politically connected firms under local political pressure or to state-owned firms without conducting stringent risk evaluations. Trust and investment companies may operate differently from commercial banks. Some listed firms often borrow from their affiliated credit companies (registered as "Other financial institutions" in our sample) under favorable terms. For these loans, loan contract terms do not truly reflect related firm risks, suggesting that collateral requirements could be symbolic and have no economic meaning. To address this issue, we exclude loans from these financial institutions progressively and re-estimate *Equation (4)*.[40] Results are reported in the Internet Appendix, Table IA.VII. Our key variables of interest, i.e. $ACR4_{il}$, $Sizeconcen_{il}$ and their interaction terms with IPO_{il}, have the same signs as before and are all statistically significant.

5.3. Endogeneity of loan contract terms

We have addressed the endogeneity of loan contract terms by excluding Maturityil and Spreadil throughout the paper, following Berger and Udell (1995). Although this mitigates endogeneity concerns related to loan contract terms, it could be argued that excluding other loan contract terms leads to the "missing variables" problem. Therefore, we move to instrumental variable (IV) Probit regressions. Technical details, results and relevance and validity of instrumental variables are reported in the Internet Appendix, Section C and Table IA.VIII. Focusing on our main variables of interest, i.e. relationship intensity $Sizeconcen_{il}$, concentration ratio $ACR4_{il}$ and their interaction terms with IPO_{il}, the results of the IV Probit regression are similar to that of the Probit regression in Column (3) of Table V. The IV Probit model results, however, differ from the benchmark model in the sense that the relationship lending variable $Sizeconcen_{il}$ loses its explanatory power after IPOs (H_0:$Sizeconcen_{il}$+$Sizeconcen_{il}$*IPO_{il}=0 cannot be rejected). This strongly supports our

[39] Monetary policy variables and regional macroeconomics variables are not included in this specification as they generally have low explanatory power in the previous regressions. Our results in this section are generally not sensitive to including these control variables. Results are available upon request.

[40] We remove *Maturity* and *Spread* in this section for endogeneity concerns. Including these variables generate largely similar results. Results are available upon request.

conclusion that informational rent extraction through relationship lending is greatly reduced after IPOs. Results for market structure are also consistent with our previous findings, i.e. the coefficient of the concentration ratio $ACR4_{il}$ is significant and positive, while the coefficient of its interaction term with IPO_{il} is significant and negative. Furthermore, more concentrated markets are again associated with higher collateral incidence even after the equity IPO of borrowing firms, as the null hypothesis H_0: $ACR4_{il}+ACR4_{il}*IPO_{il}=0$ is rejected.

6. Conclusions

Unlike existing studies which investigate if inside banks with informational monopolies charge informational rents through higher lending rates, we focus on informational rents related to collateral incidence. By employing the equity IPOs of borrowing firms as informational equalization shocks, our framework isolates the informational rent extraction hypothesis from competing theories. Our paper is the first to apply these IPOs to identify if banks charge informational rents through collateral.

Using a unique hand-collected loan-level data set of Chinese listed firms, we find a higher incidence of collateral for loans obtained from relationship lenders or in concentrated markets. Once an equity IPO equalizes information among lenders, the impact of relationship lending and market structure on the pledging of collateral is moderated. These findings confirm that informational advantages, either from relationship lending or concentrated market structures, allow inside banks to extract rents through collateral. Our results complement the findings in other studies that banks extract rents by charging higher lending rates from their informational monopolies, but that informational equalization shocks such as bond and equity IPOs reduce these rents significantly (Hale and Santos, 2009; Schenone, 2009).

We demonstrate also that rent extraction through collateral is significantly less pronounced for less risky firms. Our results indicate that inside banks strengthen their monopoly power for risky firms after the IPO, while informational rents are reduced for safer firms.

Finally, our paper also contributes to the empirical literature on the determinants of collateral in the Chinese banking markets, which have received little attention thus far.

Our results hold after controlling for a broad set of firm and loan characteristics, monetary policy variables, regional macroeconomic characteristics, as well as industry, provincial, bank-type and time fixed effects. Furthermore, we explore several alternative explanations and conduct a large number of additional robustness tests. All these do not materially change our conclusions.

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Internet Appendix to accompany

"Do banks extract informational rents through collateral?"

This Internet Appendix provides technical details and results of the propensity score matching analysis discussed in Section 4.2, self-selection of relationship lending (Section 5.1.2), sample selection bias (Section 5.2) and the instrumental variable Probit model (Section 5.3). Moreover, it presents details and results of several additional tests discussed in Section 4.2 ("difference-in-difference" tests, Table IA.I.) and Section 4.3 (corporate bond underwriting and concurrent lending, Table IA.IV).

A. Propensity score matching

This section presents the technical details of propensity score matching (e.g. Heckman et al., 1998). To allow for the existence of information asymmetries among inside and outside lenders, we divide our sample into two subsamples: pre-IPO loans and post-IPO loans, with the former presumably subjected to a higher degree of information asymmetries for non-relationship banks. Within each subsample, we estimate the propensity score of loans borrowed from relationship lenders using a Logit model. Specifically, for each sample, we regress the relationship dummy on the following covariates: *ACR4*, *FT*, *Liquidity*, *Size*, *Leverage*, *ROA*, *Age* and *Tangibility*.[41] For the sake of robustness, we further expand the covariates list by introducing their square terms.[42] Relationship dummies equal one if *Sizeconcen* is greater or equal to the sample median of the respective samples (0.25 for pre-IPO sample and 0.19 for post-IPO sample, respectively). We then match each relationship loan (treatment group) with a (set) of non-relationship loans (control group) that have the closest propensity scores to that relationship loan. The average treatment effects of relationship intensity on collateral incidence are expected to be significantly positive for the pre-IPO loans, and moderated or insignificant for the post-IPO loans.

To compute the average treatment effects, two alternative matching methods are used, i.e. "nearest neighbor" matching and "kernel" matching. We drop all loans that are outside of the common support to minimize the potential bias introduced by these loans. Bootstrap standard errors based on 50 replications are reported.

Next, we test the balancing property of covariates. The estimated average treatment effects are biased if the covariates determining participation in the treatment group are not sufficiently balanced. The standardized bias of Rosenbaum and Rubin (1985) is a common statistic to test the balance of the distribution of the covariates in both the control and treatment groups. For brevity, we only report the mean bias of the matched sample.[43] Several other overall balancing tests including

[41] Estimates on propensity scores are available upon request.

[42] The main purpose of propensity score estimation is not to predict selection into treatment as good as possible, but to balance all covariates (Augurzky and Schmidt, 2000).

[43] Standardized bias of individual covariate is available upon request.

pseudo-R2, Rubin's B and Rubin's R are also reported. All of these diagnoses confirm that the covariates of the matched sample are balanced. In more detail: the mean bias for the matched sample is below the 5% threshold; the pseudo-R^2 for the matched sample is fairly low; Rubin's B is below 25 thresholds for most of the cases, and Rubin's R is within [0.5, 2].[44] Results are reported in the Internet Appendix Table IA.II.

Finally, we test the sensitivity of our results to unobserved variables that affect both relationship lending and collateral incidence. Rosenbaum (2002) developed a bounding approach to address whether or not inference about treatment effects may be affected by unobserved factors. We focus on pre-IPO loans, because as noted by Hujer et al. (2004), sensitivity analysis for insignificant treatment effects is not meaningful. Results are reported in Internet Appendix Table IA.III. Given that the estimated treatment effect is positive for pre-IPO loans, the lower bounds (*Q_mh-*) – under the assumption that the true treatment effect has been underestimated – are less interesting (Becker and Caliendo, 2007). Therefore, we focus on the upper bounds (*Q_mh+*). We report the Rosenbaum bounds for propensity score model II with the nearest neighbor matching (*NN(20)*). The results for the bounds are similar for propensity score model I and other matching methods. The critical level e^{γ}, at which one would question the positive effect of relationship lending on collateral incidence, is 1.85, a fairly large value by normal standards (see e.g. Bharath et al., 2011, for further discussion). Note that a critical value of 1.85 does not mean that relationship lending has no effect on collateral incidence and that unobserved heterogeneity exists. It only states that the confidence interval for the treatment effect would include zero if unobserved variables caused the odds ratio of relationship lending to differ between relationship borrowers and non-relationship borrowers by a factor 1.85. We conclude that it is unlikely that our causal inference of the positive effect of relationship lending on collateral incidence for pre-IPO loans will be challenged by powerful unobserved variables.

B. Self-selection of relationship lending

This section presents technical details on Heckman's 2-stage correction model (e.g. Heckman, 1979) for self-selection of relationship lending. In a fashion similar to Presbitero and Zazzaro (2010), we define a relationship lending dummy $Rel_i = 1$ if the firm obtains at least 20% (e.g. the sample median of the relationship lending variable *Sizeconcen* that we used in our baseline regressions) of bank loans from the lender prior to the current loan. The bivariate Probit model is specified as a system of selection and outcome equations (*Rel* and *Collateral* equations, respectively), as defined in *Equation (IA.1)*):

$$Collateral_i^* = X_i\beta + \delta_1 Rel_i + \delta_2 Rel_i * IPO + \mu_{1i}$$

$$Collateral_i = I(Collateral_i^* > 0)$$

$$Rel_i^* = Z_i\gamma + \mu_{2i}$$

$$Rel_i = I(Rel_i^* > 0) \qquad \text{(IA.1)}$$

[44] Sianesi (2004) suggests that a low pseudo-R2 for the post matching sample is an indicator of balanced matching. Rubin's B is the absolute standardized difference of the means of the linear index of the propensity score in the treated and matched sample. Rubin's R is the ratio of treated to matched variances of the propensity score index. Rubin (2001) recommends that Rubin's B is less than 25 and Rubin's R lies between 0.5 and 2 for the samples to be sufficiently balanced.

$Collateral_i^*$ is a unobserved latent variable defined as a function of collateral determinants X_i (as specified in *Equation (1)*), relationship dummy Rel_i, its interaction term with *IPO*, and an error term μ_{1i}. The observed outcome $Collateral_i = 1$ if $Collateral_i^* > 0$ and zero otherwise. Rel_i^* is a unobserved latent variable modeled as a linear function of exogenous covariates Z_i and an error term μ_{2i}. $Rel_i = 1$ if $Rel_i^* > 0$ and zero otherwise. The error terms μ_{1i} and μ_{2i} are assumed to be independent and identically distributed as standard bivariate normal with correlation ρ i.e. $\mu_{1i}, \mu_{2i} \sim \emptyset_2(0, 0, 1, 1, \rho)$. The cross-equation correlation variable ρ picks up the latent factors, which jointly affect the likelihood of borrowing from relationship lenders and pledging collateral. If $\rho = 0$, a separate estimation of the structural equation by a single equation Probit model is justified. If $\rho \neq 0$, the decision to borrow from relationship lenders is related to the decision to pledge collateral due to some unobserved factors. In this instance, a joint estimation can correct this endogeneity.

Identification of the model requires that at least one exclusion restriction, i.e. at least one explanatory variable, is included in the selection equation but not in the outcome equation.[45] We use *Localavrate* as an exogenous variable that affects the decision to borrow from relationship lenders in the vector Z_i. *Localavrate* is the lagged regional average lending rate, measured at one semi-accounting year before the current loan. Its coefficient is expected to be positive as firms might prefer to borrow from their relationship lenders when conditions in regional (local) credit markets are tight. It is unlikely that *Localavrate* will affect the collateral pledged for individual current loans (see e.g. Bharath et al., 2011 for a similar instrument).[46] Other covariates in vector Z_i include firm and loan characteristics, monetary policy and regional macroeconomic variables, and fixed effects dummies.

Again, to address the endogeneity concerns of other loan contract terms, we report specifications with and without *Maturity* and *Spread*, in Panels A and B of Internet Appendix Table IA.V, respectively. Estimates of the selection equation are reported in Columns (1) and (3); those of the outcome equation are reported in Columns (2) and (4). The estimated correlation between the error terms of the two equations, i.e. ρ, is significantly negative, as the Wald-test of $\rho = 0$ is rejected at 1% in both specifications, confirming the validity of the joint estimation of relationship lending and collateral.

C. Endogeneity of loan contract terms

This section addresses the endogeneity issue of loan contract terms using IV Probit estimation. Our choices of instruments are guided by the existing literature and the specific characteristics of Chinese banking regulation. For *Maturity*, we follow Barclay et al. (1995) and employ asset maturity (*Amaturity*) as instrument, as firms may match their debt maturity with that of their assets to mitigate agency costs.[47] In

[45] Nonlinearity of the functional form allows for identification without exclusion restrictions. In this case, estimates have no structural interpretation due to the collinearity between the selection and outcome equations.

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

[47] See Bharath et al. (2011) and Barclay et al. (2003) for further discussions of the validity of using asset maturity as instrument for debt maturity. We follow Li et al. (2009) in defining asset maturity.

addition, as proposed in Dennis et al. (2000) and Brick and Ravid (1985), loan maturity is expected to be positively related to the slope of the yield curve, proxied by the term spread (*Termspread*). This spread is defined as the yield difference between the 5- and 1-year government bonds for the month when the loan is originated. Regarding the lending spread, we use as instrument the benchmark loan spread (*Benchsprd*) for maturities that correspond with that of loan *l* in the month of the loan origination. (*Benchsprd* = benchmark lending rate minus the benchmark deposit rate). Another instrument we introduce is the lagged regional average lending rate (*Localavrate*), measured at one semi-accounting year before the current loan.[48] *Benchsprd* and *Localavrate* should be correlated with the actual lending spread, but they are not likely to be related to whether or not a particular loan is collateralized.[49] Summary statistics and definitions of these instrumental variables are in Panel F of Table I.

Results of IV Probit model are reported in Internet Appendix, Table IA.VIII. Column (1) excludes *Spread* from the determinants of collateral and treats *Maturity* as the sole endogenous variable, whereas Column (2) treats both *Spread* and *Maturity* as endogenous variables.[50] Newey's efficient two-step estimator is employed to obtain coefficient estimates for both specifications. The relevance and validity of our instruments in the IV Probit model are reported at the bottom rows.[51] In both column (1) and (2), 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), validating the IV Probit approach. The results of the conditional likelihood-ratio (*CLR*) test, *K* test and Anderson-Rubin Chi square test (*AR*), all reject the null hypothesis that the coefficients of the endogenous regressors in the structural equation are (jointly) zero. We also conduct the *J* statistics test, which assesses the validity of the instruments, i.e. the null hypothesis is that the instruments are uncorrelated with the error term. In both Column (1) and (2), the *J* statistics are statistically insignificant, confirming the validity of our instruments for the endogenous loan contract term *Maturity*, or for both *Maturity* and *Spread*.

See Table I, Panel F for definitions. Missing data is replaced by the industry median for asset maturity.

[48] The People's Bank of China reports on yearly basis for each province the percentage of loans with rates below/at/above reference rates of a corresponding maturity. The actual interest rate to benchmark rate ratios are 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.

[49] *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.

[50] 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 possibilities.

[51] See Finlay and Magnusson (2009) for details on weak instrument robustness tests for limited dependent variable models.

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Table IA.I Heterogeneous dynamic of firm risks around IPOs

This table reports the mean differences in key risk factors around IPOs (*post-IPO-pre-IPO*) for both relationship dependent and non-dependent firms. Relationship dependent firms are the ones with *Sizeconcen* greater to equal to sample median, while the rest is the non-dependent firms. *** p<0.01, ** p<0.05, * p<0.1.

	ROA	Leverage	Tangibility	Liquidity	Size	Maturity	Spread	Loansize
Relationship Dependent Firms	-0.03***	0.21***	0.08***	0.23***	4.04***	0.14**	0.25**	1.06***
Relationship Non-dependent firms	-0.05***	0.20***	0.11***	0.15***	3.94***	0.19***	-0.06	0.83***
Mean difference	-0.01	-0.00	0.03	-0.08***	-0.11	0.04	0.19	-0.23

Table IA.II: Selection of observables-Propensity score matching.

This table reports average treatment effects of relationship lending on collateral incidence for pre-IPO and post-IPO loans. Propensity Score Model I in Panel A employs the following variables: ***ACR4, FT, Liquidity, Size, Leverage, ROA, Age*** and ***Tangibility***. The Propensity Score Model II in Panel B includes all variables used in Panel A and the square terms of these variables (except the square term of FT). Logit regression is adopted in both panels. Bootstrap standard errors based on 50 replications are reported. NN(20) and NN(50) are the nearest neighbor matching estimators with 20 and 50 nearest neighbors. Epanechnikov kernel with bandwidth 0.06 is applied for the kernel matching estimator. Observations off common support are discarded. All balancing tests are based on matched samples. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Propensity Score Model I						
	Pre-IPO loans			Post-IPO loans		
	NN(20)	NN(50)	Kernel	NN(20)	NN(50)	Kernel
ATE	0.126***	0.116***	0.115***	-0.005	-0.005	-0.008
Std.Err.	(0.033)	(0.032)	(0.029)	(0.012)	(0.014)	(0.012)
Pseudo R2	0.006	0.004	0.006	0.002	0.002	0.001
Mean Bias	4.7	3.2	4.3	3.1	2.5	2.0
Rubin's B	17.6	15.0	18.3	10.7	9.5	8.0
Rubin's R	0.99	1.16	1.01	1.28	1.46	1.36
Panel B: Propensity Score Model II						
ATE	0.103***	0.102***	0.108***	0.007	-0.002	0.002
Std.Err.	(0.033)	(0.036)	(0.037)	(0.015)	(0.014)	(0.011)
Pseudo R2	0.013	0.013	0.007	0.002	0.002	0.002
Mean Bias	3.3	4.4	3.3	1.8	1.4	1.9
Rubin's B	27.0*	27.4*	20.2	11.0	11.2	9.8
Rubin's R	1.16	1.23	1.04	1.42	1.41	1.44

Table IA.III: Sensitivity test-Rosenbaum bounds.

This table reports results for the Rosenbaum bounds test for propensity score model II with nearest neighbor matching (NN(20)). e^{γ} is the odds of differential assignment due to unobserved factors. *Q_mh+* and *Q_mh-* are the upper and lower bounds of the Mantel-Haenszel statistic. With increasing e^{γ}, the bounds move apart, reflecting uncertainty about the test-statistics in the presence of hidden bias. *p_mh+* and *p_mh-* are significance levels for upper and lower bounds.

e^{γ}	Q_mh+	Q_mh-	p_mh+	p_mh-
1	4.51	4.51	0.00	0.00
1.05	4.24	4.78	0.00	0.00
1.1	3.98	5.04	0.00	0.00
1.15	3.74	5.29	0.00	0.00
1.2	3.51	5.53	0.00	0.00
1.25	3.29	5.77	0.00	0.00
1.3	3.07	6.00	0.00	0.00
1.35	2.87	6.22	0.00	0.00
1.4	2.68	6.43	0.00	0.00
1.45	2.49	6.64	0.01	0.00
1.5	2.31	6.84	0.01	0.00
1.55	2.13	7.04	0.02	0.00
1.6	1.97	7.23	0.02	0.00
1.65	1.80	7.42	0.04	0.00
1.7	1.64	7.60	0.05	0.00
1.75	1.49	7.78	0.07	0.00
1.8	1.34	7.95	0.09	0.00
1.85	1.20	8.13	0.12	0.00

Table IA.IV: Corporate bond underwriting and concurrent lending

This table reports the results for samples of loans issued before corporate bond IPOs using Probit model. Column (1) reports results for full sample. Column (2) report results for sample of firms that borrowed both before and after their equity IPOs. In both columns, loans borrowed after corporate bond IPOs are excluded. Results for firm characteristics and fixed effects dummies are not reported to save space. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Loans before corporate bond IPOs	
	All firms	Firms that borrowed both before and after equity IPO
VARIABLES	(1)	(2)
Sizeconcen	0.642***	1.531***
	(0.190)	(0.326)
ACR4	4.651***	12.911***
	(1.228)	(2.637)
Sizeconcen*IPO	-0.511**	-0.813**
	(0.201)	(0.398)
ACR4*IPO	-3.777***	-4.129*
	(1.022)	(2.460)
First	0.542***	1.083***
	(0.154)	(0.252)
First*IPO	-0.562***	-1.079***
	(0.160)	(0.288)
Switch	0.106	0.500***
	(0.121)	(0.188)
Switch*IPO	-0.182	-0.592***
	(0.128)	(0.222)
Numlender	0.027***	0.111***
	(0.008)	(0.028)
IPO	2.086***	3.371**
	(0.601)	(1.425)
FT	-0.631***	-0.731***
	(0.052)	(0.255)
Constant	-0.341	-7.682
	(0.920)	(182.973)
Fixed effects dummies	Industry, Province, Bank Type, Time	
Firm characteristics	Yes	Yes
Monetary policy variables	No	No
Regional macro variables	No	No
Other contract terms	No	No
Observations	7,453	1,606
Pseudo R2	0.270	0.401
H_0:*Sizeconcen+Sizeconcen*IPO*=0	0.131*	0.719***
H_0: *ACR4+ACR4*IPO*=0	0.875	8.781***

Table IA.V: Self-selection of relationship lending

This table reports results controlling for self-selection of relationship lending. Variables in the outcome equation are the same as *Equation (4)*, except that *Sizeconcen* is replaced by the *Rel* dummy. *Rel* equals 1 if *Sizeconcen* is above sample median (0.2), and equals 0 othersize. Variables in the selection equation (vector Z_i) include *ACR4*, *IPO*, firm and loan characteristics, a monetary policy variable (*RRR*), regional macroeconomic variables, a set of fixed effects dummies and one instrumental variable *Localavrate*. Panel A reports results including *Maturity* and *Spread*, while Panel B excludes them. Results for fixed effects dummies are not reported to save space. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Panel A: With loan contract terms		Panel B: Without loan contract terms	
	Selection equation Rel	Outcome equation Collateral	Selection equation Rel	Outcome equation Collateral
VARIABLES	(1)	(2)	(3)	(4)
Rel		1.314***		1.225***
		(0.247)		(0.261)
Rel*IPO		-0.521***		-0.494***
		(0.148)		(0.150)
Localavrate	0.115***		0.108***	
	(0.040)		(0.040)	
ACR4	2.383***	4.999***	2.308***	5.059***
	(0.746)	(1.178)	(0.744)	(1.182)
ACR4*IPO		-3.198***		-3.262***
		(0.935)		(0.941)
First		0.478***		0.433**
		(0.175)		(0.177)
First*IPO		-0.564***		-0.513***
		(0.182)		(0.184)
Switch		0.130		0.092
		(0.116)		(0.118)
Switch*IPO		-0.173		-0.171
		(0.122)		(0.124)
Numlender		0.002		-0.013
		(0.028)		(0.028)
Numlender*IPO		0.015		0.024
		(0.029)		(0.029)
IPO	0.005	1.870***	0.027	1.870***
	(0.058)	(0.561)	(0.058)	(0.565)
FT	-0.038	-0.551***	-0.014	-0.554***
	(0.041)	(0.054)	(0.041)	(0.052)
Liquidity	0.290**	-0.491***	0.220*	-0.553***
	(0.130)	(0.148)	(0.129)	(0.148)
Size	-0.040*	-0.192***	-0.032	-0.191***
	(0.023)	(0.029)	(0.023)	(0.029)

Table IA.V: continued

	Panel A: With loan contract terms		Panel B: Without loan contract terms	
	Selection equation Rel	Outcome equation Collateral	Selection equation Rel	Outcome equation Collateral
VARIABLES	(1)	(2)	(3)	(4)
Leverage	0.184*	0.828***	0.249**	0.928***
	(0.104)	(0.132)	(0.104)	(0.135)
ROA	-1.314***	-0.727**	-1.248***	-0.736**
	(0.232)	(0.302)	(0.230)	(0.307)
Age	0.006	-0.379***	-0.000	-0.398***
	(0.049)	(0.058)	(0.049)	(0.059)
Tangibility	-0.163	-0.745***	-0.201	-0.784***
	(0.156)	(0.179)	(0.156)	(0.181)
Maturity	0.097***	0.134***		
	(0.023)	(0.030)		
Spread	-0.052***	0.046***		
	(0.016)	(0.017)		
Loansize	-0.023	-0.076***	-0.007	-0.063***
	(0.017)	(0.020)	(0.016)	(0.019)
Loanconcen	1.083***	1.398***	1.180***	1.505***
	(0.288)	(0.421)	(0.286)	(0.428)
RRR	8.810***	-2.897	8.797***	-2.713
	(2.440)	(2.863)	(2.430)	(2.875)
Repo	-0.091***	0.075***	-0.092***	0.069**
	(0.025)	(0.027)	(0.025)	(0.027)
CPI	-2.843**	1.896	-2.444*	2.332
	(1.398)	(1.451)	(1.395)	(1.450)
NPLratio	1.407	-0.916	1.214	-0.940
	(0.955)	(1.089)	(0.952)	(1.091)
Realgdpindex	0.546	1.151	0.888	1.507
	(1.318)	(1.378)	(1.316)	(1.381)
Constant	-0.185	-3.051	-0.471	-3.021
	(1.637)	(1.867)	(1.632)	(1.874)
Fixed effects dummies	Industry, Province, Bank type, Time			
Observations	8,765	8,765	8,777	8,777
Rho	-0.508***		-0.472***	
Wald test of rho=0	chi2(1)=10.02		chi2(1)=8.14	
Prob>chi2	0.002		0.004	
H_0: *ACR4+ACR4*IPO*=0	1.801**		1.796**	
H_0:*Rel+Rel*IPO*=0	0.793***		0.7305***	

Table IA.VI: Alternative samples-Firms borrowed both before and after IPO

This table reports the results for sample of firms that borrowed both before and after their equity IPOs. Panel A reports results for all loans. Panel B further restricts this sample to loans around IPOs dates. Results for firm characteristics and fixed effects dummies are not reported to save space. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Firms borrowed both before and after IPO			
	Panel A: All loans	Panel B: Loans around IPOs dates		
		One loan before and one after equity IPO	Two loans before and two after equity IPO	Three loans before and three after equity IPO
VARIABLES	(1)	(2)	(3)	(4)
Sizeconcen	1.532***	2.293**	1.099**	1.173***
	(0.324)	(0.921)	(0.534)	(0.441)
ACR4	12.211***	14.652	11.515**	7.357*
	(2.543)	(9.731)	(5.416)	(4.284)
Sizeconcen*IPO	-0.713*	-1.108	-1.165*	-1.076*
	(0.394)	(1.208)	(0.683)	(0.552)
ACR4*IPO	-4.224*	-0.766	-8.850*	-8.722**
	(2.405)	(8.008)	(4.901)	(4.031)
First	1.121***	2.497***	1.439***	0.854**
	(0.251)	(0.842)	(0.499)	(0.378)
First*IPO	-1.069***	-1.086	-1.351**	-0.860*
	(0.286)	(0.873)	(0.564)	(0.447)
Switch	0.491***	-0.815	-0.049	0.277
	(0.188)	(0.623)	(0.381)	(0.283)
Switch*IPO	-0.588***	-0.138	-0.423	-0.465
	(0.220)	(0.831)	(0.494)	(0.376)
Numlender	0.114***	0.367**	0.176**	0.131**
	(0.027)	(0.158)	(0.084)	(0.058)
IPO	3.353**	1.439	6.374**	6.165***
	(1.394)	(4.649)	(2.837)	(2.332)
FT	-0.683***	-5.019***	-2.392***	-1.880***
	(0.244)	(1.291)	(0.555)	(0.410)
Constant	-7.514	-14.636	-12.967	-8.227
	(159.820)	(326.925)	(326.330)	(242.200)
Fixed effects dummies	Industry FE, Province FE, Bank Type FE, Time FE			
Firm characteristics	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No
Monetary policy variables	No	No	No	No
Regional macro variables	No	No	No	No
Other loan contract terms	No	No	No	No
Observations	1,663	215	421	564
Pseudo R2	0.403	0.553	0.452	0.364
H_0:*Sizeconcen+Sizeconcen*IPO*=0	0.819***	1.184	-0.066	0.096
H_0: *ACR4+ACR4*IPO*=0	7.987***	13.886	2.665	-1.365

Table IA.VII: Alternative Samples-Excluding non-commercial basis loans

This table reports results for samples of loans from various bank types. We exclude progressively loans that are less likely to be issued under commercial basis. The model specification is based on *Equation (4)* excluding: *Maturity*, *Spread*, monetary variables, and regional macroeconomic variables. Including these variables does not affect our results. Column (1) excludes loans borrowed from state owned banks (SOCBS). Column (2) excludes loans from policy banks (PBs). Column (3) excludes loans from both policy banks and state owned banks. Column (4) further excludes loans borrowed from trust and investment companies (TICs). Column (5) further excludes other financial companies (Other), which leaves loans from joint-stock commercial banks, city commercial banks, rural commercial (cooperative) banks, and foreign banks remaining. Results for firm characteristics and fixed effects dummies are not reported to save space. The equation is estimated with the Probit model. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Excluding SOCBs	Excluding PBs	Excluding SOCBs&PBs	Excluding SOCBs&PBs &TICs	Excluding SOCBs&PBs &TICs&Other
VARIABLES	(1)	(2)	(3)	(4)	(5)
Sizeconcen	1.323***	0.556***	0.792**	0.958**	0.957**
	(0.344)	(0.194)	(0.368)	(0.388)	(0.393)
ACR4	11.231***	5.047***	10.203***	9.115***	9.108***
	(1.972)	(1.212)	(2.076)	(2.173)	(2.195)
IPO*Sizeconcen	-1.229***	-0.409**	-0.680*	-0.722*	-0.706*
	(0.358)	(0.203)	(0.385)	(0.406)	(0.412)
IPO*ACR4	-7.334***	-3.153***	-6.541***	-4.875***	-5.358***
	(1.718)	(1.022)	(1.779)	(1.871)	(1.881)
First	0.703***	0.501***	0.528**	0.682***	0.616**
	(0.227)	(0.157)	(0.246)	(0.257)	(0.262)
IPO*First	-0.673***	-0.474***	-0.446*	-0.605**	-0.550**
	(0.234)	(0.162)	(0.254)	(0.264)	(0.269)
Switch	0.316*	0.030	0.070	0.077	0.110
	(0.190)	(0.123)	(0.207)	(0.217)	(0.221)
IPO*Switch	-0.444**	-0.126	-0.263	-0.277	-0.308
	(0.200)	(0.129)	(0.217)	(0.227)	(0.231)
Numlender	0.024**	0.026***	0.034***	0.027**	0.028**
	(0.009)	(0.007)	(0.010)	(0.011)	(0.012)
IPO	4.511***	1.731***	3.773***	2.811**	3.039***
	(1.017)	(0.604)	(1.065)	(1.120)	(1.127)
FT	-0.520***	-0.565***	-0.440***	-0.477***	-0.476***
	(0.070)	(0.048)	(0.075)	(0.083)	(0.084)
Constant	-9.580	-0.111	-8.429	-8.433	-6.706
	(165.908)	(0.917)	(95.904)	(92.578)	(80.646)
Fixed effects dummies	Industry, Province, Bank Type, Time				
Firm characteristics	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
Monetary policy variables	No	No	No	No	No
Regional macro variables	No	No	No	No	No
Other loan contract terms	No	No	No	No	No
Observations	4,098	8,273	3,573	3,274	3,132
Pseudo R2	0.313	0.286	0.317	0.322	0.312
H_0: *ACR4+IPO*ACR4*=0	3.897***	1.894**	3.662***	4.239***	3.750***
H_0:*Sizeconcen+IPO*Sizeconcen*=0	0.094	0.147*	0.112	0.238*	0.251*

Table IA.VIII: Endogeneity of loan contract terms

This table report IV probit regression results, treating other loan contract terms as endogenous variables. Column (1) treats ***Maturity*** as the sole endogenous variable, assuming that ***Spread*** does not affect collateral incidence. Column (2) treats both ***Spread*** and ***Maturity*** as endogenous variables. The instruments for ***Maturity*** are asset maturity (***Amaturity***) and term spread (***Termsprd***). Instruments for ***Spread*** are the local average lending rate (***Localavrate***) and benchmark loan spread (***Benchsprd***). Definitions and summary statistics for these instrumental variables are reported in Table I, Panel F. Results for fixed effects dummies and first stage estimations of IV probit regression are not reported to save space. They are available upon request. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	IV Probit	
VARIABLES	(1)	(2)
$\widehat{\text{Maturity}}$		0.597**
		(0.273)
$\widehat{\text{Spread}}$	0.996**	0.746***
	(0.426)	(0.271)
Sizeconcen	0.503**	0.591**
	(0.250)	(0.242)
ACR4	4.972***	5.279***
	(1.314)	(1.320)
Sizeconcen*IPO	-0.501**	-0.608**
	(0.251)	(0.253)
ACR4*IPO	-3.013***	-3.364***
	(1.099)	(1.098)
First	0.394*	0.345
	(0.217)	(0.223)
First*IPO	-0.446**	-0.480**
	(0.225)	(0.228)
Switch	0.530***	0.358**
	(0.191)	(0.146)
Switch*IPO	-0.392***	-0.368**
	(0.149)	(0.148)
Numlender	0.076	-0.016
	(0.049)	(0.039)
Numlender*IPO	-0.018	0.021
	(0.040)	(0.037)
IPO	1.648**	1.920***
	(0.684)	(0.683)
FT	-0.671***	-0.534***
	(0.067)	(0.056)
Liquidity	0.090	-0.242
	(0.329)	(0.201)
Size	-0.260***	-0.172***
	(0.038)	(0.036)
Leverage	0.372	0.667***
	(0.262)	(0.155)

Table IA.VIII: Continued

	IV Probit	
VARIABLES	(1)	(2)
ROA	-1.460***	-1.077***
	(0.335)	(0.351)
Age	-0.452***	-0.521***
	(0.071)	(0.064)
Tangibility	-0.587**	-0.788***
	(0.284)	(0.222)
Loansize	-0.200***	-0.107***
	(0.060)	(0.024)
Loanconcen	1.471***	1.665***
	(0.523)	(0.475)
RRR	-3.191	-0.083
	(3.273)	(3.755)
Repo	0.045	0.068**
	(0.030)	(0.031)
CPI	-1.791	-1.389
	(1.949)	(1.839)
NPLratio	0.891	-0.905
	(1.309)	(1.382)
Realgdpindex	-1.625	-0.290
	(1.858)	(1.647)
Constant	0.385	-2.186
	(2.193)	(2.468)
Observations	8,159	8,159
Fixed effects dummies	Industry, Province, Bank Type, Time	
H_0:*Sizeconcen*+*Sizeconcen***IPO*=0	0.002	-0.017
H_0: *ACR4*+*ACR4***IPO*=0	1.959***	1.914**
H_0:*First*+*First***IPO*=0	-0.052	-0.136
H_0:*Switch*+*Switch***IPO*=0	0.138	-0.009
Wald test (p-value)	Chi2(1)=5.48 (0.0192)	Chi2(2)=20.36 (0.0000)
CLR (p-value)	6.12 (0.0146)	23.94 (0.0000)
K (p-value)	Chi2(1)=6.12 (0.0134)	Chi2(2)=23.23 (0.0000)
J (p-value)	Chi2(1)=0.00 (0.9488)	Chi2(2)=1.81 (0.4041)
AR (p-value)	Chi2(2)=6.12 (0.0469)	Chi2(4)=25.04 (0.0000)

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