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Liquidation Values, Claim Priority, and Productivity

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We investigate the link between liquidation values, claim priority, and productivity using a large matched firm-loan dataset for the US. Loans in sectors with higher liquidation values are less likely to be collateralized or monitored and have better terms, consistent with a model of claim priority as a contracting device. Exploiting the lifting of bank branching restrictions as a natural experiment, we find that collateral has become more important with deregulation. This has potential macroeconomic implications: liquidation values are negatively correlated with R&D intensity and productivity growth, pointing to frictions in the allocation of capital even in normal times.

JEL: G21, G32

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Collateral plays an important role in loan contracts by reducing bank losses if a borrower defaults. It also enables borrowers to receive more favourable loan terms, all else equal. Pledgeable assets, however, may differ strongly in the values a bank is able to recover from their liquidation. Less specific firm assets are likely to be more redeployable by other firms and have more liquid secondary markets with lower transaction costs. As a result, they likely yield higher average liquidation values.[1]

Firms with less redeployable assets, however, may be able to contract around this disadvantage by allowing lenders more extensive creditor control rights. These can take the form of a higher contract seniority in the claimant structure or interference with management decisions through covenants or borrower base arrangements. Both protect the bank from losses in adverse scenarios.

But how important are liquidation values in a sophisticated financial market like the US, and how significant are the arising credit market frictions? We find that firms in sectors with more redeployable assets receive more credit and considerably better loan terms, irrespective of firm fundamentals and unobserved factors on the industry, state and bank level. Lower liquidation values lead banks to keep firms on a short leash by using senior claims and more intense monitoring. We show that these firms are further unable to compensate with internal cash flows or equity financing. Strikingly, liquidation values are negatively correlated with productivity growth and R&D expenditure. This points to considerable frictions in the allocation of capital with potential adverse macroeconomic implications.

To illustrate the issue, we construct a simple model where liquidation values determine claim priority and loan contract terms. We show that firms can use

[1] A large body of literature provides evidence for this argument. Many assets are sector-specific and homogenous within industries (Valerie A. Ramey and Matthew D. Shapiro, 2001; Joshua D. Rauh and Amir Sufi, 2011). Since liquidation values depend on secondary market demand (Andrei Shleifer and Robert W Vishny, 1992; Efraim Benmelech and Nittai K. Bergman, 2011), it is not surprising that non-specific assets such as real estate have been found to be a particularly important type of collateral (Eric S. Rosengren and Joe Peek, 2000; Jie Gan, 2007; Thomas Chaney, David Sraer and David Thesmar, 2012; Murillo Campello and Erasmo Giambona, 2013). See also Efraim Benmelech, Mark J. Garmaise and Tobias J. Moskowitz (2005).

the seniority on their debt claims as a contractual device to compensate for lower liquidation values, but only up to a point. The use of priority claims is likely to be especially important in sectors with lower liquidation values, because they increase the likelihood for banks to recover *any* value in case a firm defaults. We find evidence for this prediction empirically: liquidation values are negatively associated with collateralization, financial covenants, and borrower base contracts.

Our findings are consistent across alternative definitions of industry and contract-level measures of asset redeployability. Exploiting a hitherto unused package of the Dealscan database, we are able to observe the collateral actually used in the loan contract, not just the potentially pledgeable assets on its balance sheet. We can thus directly observe how other contract terms vary with the type of pledged asset, conditional on a loan being secured.

Teasing out the importance of collateral clearly represents an econometric challenge, because loan terms are jointly determined. Even if we find our proxies of liquidation values to have an impact on loan terms, our results may be driven by unobserved time-varying firm determinants like differences in credit risk or credit demand. We attempt to accommodate these concerns twofold.

First, we stack the odds against us by employing an extremely stringent set of control variables and fixed effects. We include firm- and loan-level control variables common in the literature, as well as squared and cubed values to account for potential non-linearities. Further, we successively saturate our model with a rich set of $industry \times year$, $bank \times year$, and $state \times year$ fixed effects in the spirit of Gabriel Jiménez, Steven Ongena, José-Luis Peydró and Jesús Saurina (2014) to absorb potential unobserved demand shocks biasing our results. While the structure of our dataset does not allow controlling for $firm \times year$ dummies, we conduct a battery of exercises to show that these findings cannot be explained by firms with lower debt capacity demanding less credit – particularly given that *all* loan terms improve with liquidation values (see e.g. Patrick Bolton, Hui Chen and Neng Wang, 2014). Our results are robust across many different empirical specifications and also hold in classic capital structure regressions.

Second, we use the staggered implementation of the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) as an exogenous shock to the relative importance of liquidation values for banks' lending decisions. The IBBEA allowed states considerable leeway in implementing bank branching deregulation, which enabled banks from outside states to compete with local lenders. We make use of the fact that the pace of implementation reflected the political power struggle between small and large banks, as well as other special interests, and is unrelated to individual loan contracts (Christian A Johnson and Tara Rice, 2008; Randall S. Kroszner and Philip E. Strahan, 2014). The deregulation process increased competition and house prices, but also the distance between lenders and borrowers, as well as banks' reliance on hard information such as credit ratings. It also raised the costs of monitoring firms with lower, more uncertain liquidation values. Using an index for the state-wise implementation of the IBBEA constructed by J. Hendrickson and M.W. Nichols (2011) for 1992 to 2010 allows us to treat the lifting of branching restrictions as a quasi-natural experiment.[2] We find that the IBBEA implementation has had an amplifying effect on the importance of liquidation values on loan terms. This suggests that the well-documented benefits of US banking deregulation may have disproportionally fallen on sectors with structurally more redeployable assets and exacerbated existing frictions.

Our paper is closely related to recent work by Geraldo Cerqueiro, Steven Ongena and Kasper Roszbach (2014), Campello and Giambona (2013), and Efraim Benmelech and Nittai K. Bergman (2009), who investigate the importance of liquidation values on corporate leverage and loan terms. We generalize the findings of Cerqueiro, Ongena and Roszbach (2014), who study a legal reform in Swe-

[2]The index we use covers a longer time period than the one presented in Tara Rice and Philip E. Strahan (2010), but our results are not driven by the choice of branching deregulation index. In fact, the two are almost equivalent for the overlapping period from 1994 to 2005.

den that exogenously decreased firm liquidation values in *floating lien* contracts. They find that as a result, loan terms deteriorated and banks monitored firms *less* stringently. However, the change in law reduced the claim priority of floating lien contracts, but also extended the pool of eligible assets. The enlarged, post-reform asset menu included cash, financial assets, and real estate – which have higher liquidation values and lower monitoring needs. As a result, it is not clear whether the decreased monitoring they observe is because of the change in claim priority or inclusion of more redeployable assets. Our merged dataset allows us to show that both independently matter for loan contract terms.

Our work also adds to the relatively recent empirical literature on liquidation values and asset redeployability.[3] The importance of different types of collateral for real economic outcomes has also been highlighted by a strand of recent case studies on reforms broadening the type of collateral in loan contracts (Campello and Larrain, 2016; Calomiris et al., 2015). Motivated by their findings, we show that even in a financial market as sophisticated as the US, liquidation values play a major role in shaping loan terms across sectors.

We also contribute to the rich literature on the effects of the step-wise banking deregulation in the US. The lifting of bank branching restrictions has been associated with higher per capita growth (Jith Jayaratne and Philip E Strahan, 1996); fostering entrepreneurship (Sandra E. Black and Philip E. Strahan, 2002; William R. Kerr and Ramana Nanda, 2009; Nicola Cetorelli and Philip E. Strahan, 2006); lower state-level volatility (Donald Morgan, Bertrand Rime and Philip E. Strahan, 2004); decreased interest rates for small businesses (Rice and Strahan, 2010); more efficient capital allocation (Viral V. Acharya, Jean Imbs and Jason Sturgess, 2011); and decreased inequality (Thorsten Beck, Ross Levine and Alexey Levkov, 2010). Our findings suggest that deregulation has, however, also

[3] No consensus has emerged as of yet regarding the terminology, partly because many contributions center around specific reforms. Jos M. Liberti and Atif R. Mian (2010) divide firm assets into specific and non-specific. Murillo Campello and Mauricio Larrain (2016) and Charles W. Calomiris, Mauricio Larrain, Jos Liberti and Jason Sturgess (2015) differentiate between movable and immovable assets. Rauh and Sufi (2011) use asset similarity and Efraim Benmelech (2009) asset salability. The concepts are equivalent for all practical reasons, and we consistently use the terms redeployability and liquidation values in this paper.

increased the importance of collateral with the shift towards more transaction-based banking. We believe to be the first to show this effect empirically. The results add to the evidence in R. Gaston Gelos and Alejandro M. Werner (2002), who show that financial liberalization increased the role of real estate as collateral in the Mexican manufacturing sector.

I. Claim Priority as Contracting Device: A Simple Illustration

We start our investigation by constructing a simple model to illustrate the link between liquidation values, claim priority, and loan contract terms. We show that by allowing creditors to take a more senior position in their claimant structure, firms can contract around frictions arising from differences in liquidation values – at least up to an extent. Below a certain threshold, liquidation values are too low for firms to compensate with claim priority, and borrowers are shut out of the credit market.

We establish this intuition in a set-up similar to Vikrant Vig (2013), who analyses the effect of secured and unsecured debt on loan terms. In our model, claim priority can be interpreted as any type of creditor interference, motivated by the empirical literature on how creditors influence corporate policies through control rights (Sudheer Chava and Michael R Roberts, 2008; Greg Nini, David C. Smith and Amir Sufi, 2009; Michael R. Roberts and Amir Sufi, 2009; Greg Nini, David C. Smith and Amir Sufi, 2012). As we will see later, claim priority could take the form of collateralization of firm assets, inclusion of loan covenants, or other contractual features such as a borrowing base, which implies strict monitoring of asset values. Our prediction that more senior credit claims are more likely to be found when assets are highly specific and have lower liquidation values goes back to Oliver E Williamson (1988).

Consider a continuum of firms which can each invest into single fixed size investment projects I_1 in period 0. In period 2, the investment yields a verifiable cash flow C_1 with a likelihood of θ and 0 otherwise. If the project succeeds, firms produce and all assets are fully depreciated. If the project fails, assets are not depreciated and can be sold in period 2 by the bank at their liquidation value. The liquidation value is a fraction $1 \geq \delta > 0$ of the original value I_1. Firms have no own funds and need to finance I_1 with credit, obtained from some bank 1.

Consider the existence of a second debt claim on the firm, which is only relevant here to investigate the issue of seniority. If I_1 is undertaken, firms can undertake another investment project in period 1, I_2, that will be financed by bank 2. It yields a verifiable cash flow C_2, which is perfectly correlated with C_1 while $I_2 = I_1$. All assets of I_2 are completely depreciated in period 2, irrespectively of the state of the world. The existence of this possible future project is known in period 0. In period 2, banks obtain the repayments $R_1 \leq C_1$ and $R_2 \leq C_2$ if the project succeeds, and a fraction of the liquidation value of the firm's assets otherwise.

Assume that both investment projects have positive NPVs for all firms:

$$I_1 < \theta C_1 + (1-\theta)\delta I_1 \tag{1}$$

and

$$I_2 < \theta C_2 \tag{2}$$

The first loan can be either of low or high seniority. For simplicity, assume that the second loan cannot have a higher seniority than the first one.[4] In practice, a high seniority can also be thought of as a contract secured by collateral, involving covenants or borrower base arrangements.[5] If both banks offer low seniority loans, they obtain liquidation proceeds according to the fraction that their claims make up in the total company debt, $\frac{I_1}{I_1+I_2} = \frac{I_2}{I_1+I_2} = 0.5$. For a high se-

[4]This is intuitive if lenders compete along the seniority ladder to maximize their proceeds in the case of default. Our results, however, do not depend on this assumption.

[5]Collateralization and borrower base contracts maximize liquidation proceeds in the case of default, while monitoring through covenants or a borrower base enable the bank to interfere with management decisions.

niority loan, banks obtain the entire proceeds from asset liquidation in the case of bankruptcy.

No bank can formulate repayment claims that exceed the cash flow of the successful investment project they financed. Assume everyone is risk neutral, there is no time preference, and the interest rate at which banks obtain funds is normalized to zero. Banks are competitive and obtain a zero expected profit on all loan contracts offered.

Consider the case where bank 1 provides a high seniority loan in period 0, and bank 2 cannot interfere in the collateral claims from investment I_1. As a result, bank 2 grants credit with repayment of

$$R_2 = \frac{I_1}{\theta} \tag{3}$$

The repayment claim demanded by bank 1 on its high seniority loan is then

$$R_1 = I_1 \left[\frac{1}{\theta} + \left(1 - \frac{1}{\theta} \right) \delta \right] \tag{4}$$

If loan 1 has low seniority, bank 2 also offers a loan contract, and will be able to claim a fraction of the assets I_1 in case the project fails. This will lead bank 2 to ask for a lower repayment claim. If bank 1 would not anticipate the offer, there would be a wealth transfer from bank 1 to the firm, since it would face an expected loss or negative NPV on the loan. However, bank 1 anticipates the offer by bank 2 and R_1 is increased accordingly. With both investment volumes and seniorities being equal, the repayment claims are equivalent:

$$R_1 = R_2 = I_1 \left[\frac{1}{\theta} + \left(1 - \frac{1}{\theta} \right) \delta 0.5 \right] \tag{5}$$

Insight 1: Lower liquidation values are always associated with a higher interest rate for loans of the same seniority. Equations 4 and 5 shows that a greater δ increases the interest rate on high and low seniority loans of bank 1, since $\left(1-\frac{1}{\theta}\right)$ is a negative term for all the range of values θ can take.

The repayment requested by bank 1 on a low seniority loan will be higher than on a high seniority loan for all parameter values. The profit function for a low seniority loan by bank 1 is given by

$$\Pi_1 = 0 = -I_1 + \theta C_1 + (1-\theta)\,\delta I_1 0.5 \tag{6}$$

Rearranging yields the minimum δ for which a low seniority loan will still be offered:

$$\delta = \frac{I_1 - \theta C_1}{(1-\theta)\,I_1 0.5} \tag{7}$$

Insight 2: There is a limiting value of the liquidation factor δ below which only high but no low seniority loans are offered. In our empirical estimation this implies the prediction that lower liquidation values are more likely to be associated with collateralization, borrower base arrangements, and covenants.

It follows that for small values of δ, only high seniority loans will be relevant. The lowest possible value for which any contract will be offered can be found by solving

$$\Pi_1 = 0 = -I_1 + \theta C_1 + (1-\theta)\,\delta I_1 \tag{8}$$

for δ:

$$\delta = \frac{I_1 - \theta C_1}{(1-\theta)\,I_1} \tag{9}$$

Insight 3: There is a second, lower threshold of δ for which no loan will be profitable at all. Within our model, this implies that lower liquidation values negatively impact the likelihood of a loan being granted. Empirically, we expect to observe an inverse relationship between liquidation values and loan volume.[6]

Figure 1 illustrates the two threshold values for liquidation values and their impact on loan terms. The two curves represent distributions of liquidation values for two different sectors. The light colored, thick curve represents the distribution for firms in an industry with a high share of *Machinery & Equipment* and low liquidation values (such as biotechnology). The black thin curve represents firms in an industry that is *Land & Building* intensive, and has higher average liquidation values (such as department stores). In the latter, firms are more likely to receive credit and low seniority contracts.

As the distributions show, some industries may be locked out of the credit market to a significant extent even though their investment projects have the same positive net present values as those of other firms. Their loan applications are rejected, or come at inferior terms, only because they operate in an industry whose technology forces them to use more specific assets with lower liquidation values. Empirically, this could also take the shape of receiving smaller loans, all else equal. Inferior terms may come, for example, with higher interest rates and more stringent seniority requirements as well as shorter maturities, which we did not explicitly model here. We investigate these effects empirically in section III

To illustrate the effect of liquidation values on claim seniority and loan terms, consider an exogenous shift to these distributions. We argue below that bank branching deregulation leads to such a shift due to its impact on lender characteristics, competition, and house prices. In particular, the lifting of branching restrictions may have shifted the distribution of the *Land & Building* intensive industry to the right (a larger θ), because deregulation is associated with increases in house prices that push up liquidation values (Giovanni Favara and Jean Imbs, 2015). The distribution of the *Machinery & Equipment* intensive sec-

[6] Our dataset does not allow us to observe loan applications directly. However, we tried to construct somewhat crude measures of loan-to-value ratios and found similar results to our loan volume estimations (available on request).

tor may have shifted to the left, because the headquarters of banks that newly enter the market have a greater distance to the borrower. This is likely to be associated with lower informational capacities (Viral V Acharya, Anthony Saunders and Iftekhar Hasan, 2002) and problems to realize the full liquidation values when banks enter new states.[7] In the model, this would be reflected in a decrease in θ for the *Machinery & Equipment* intensive sector. The expected effect of the distributional shifts would be that firms in sectors with a higher share of *Land & Buildings* (*Machinery & Equipment*) receive superior (inferior) loan terms, more credit and contracts with lower (higher) seniority. We investigate these effects empirically in section IV

II. Data and Variable Construction

A. Data Sources

The source of our detailed loan information is Thomson Reuters LPC Dealscan data base, which includes the terms of more than 240,000 contracts.[8]

Firm level data comes from Standard & Poor's Compustat North American Annual Fundamentals and Ratings data bases. As standard in the literature, we exclude financial firms (SIC 6000-6999), regulated utilities (SIC 4900-4999), and public administration (SIC >9000). We drop all non-US firms and firm-years with negative assets. To minimize the impact of outliers, we exclude firm-years with total asset growth exceeding 200% or Tobin's Q larger than 10 and winsorize the balance sheet variables at the 1st and 99th percentiles. [9] Additional information on ratings is obtained from Mergent's Fixed Income Securities Database (FISD) database.

[7] Alternatively, part of the liquidation discount could be the minimum amount of monitoring costs or other transaction costs resulting from a lack of information. As in Robert Hauswald and Robert Marquez (2006) they might be an increasing function of the borrower lender distance. It may also discourage monitoring and lead to a greater importance of hard information at the expense of personal relationships.

[8] Variables from several individual Dealscan files are used here: Facility, Current Facility Pricing, Lender Shares, Borrower Base, Facility Security, Financial Covenants, and Package.

[9] The results are not driven by the choice of winsorization percentile.

Dealscan files are matched to these datasets with the Dealscan Compustat link file from Chava and Roberts (2008) and an additional match and merge algorithm to increase the number of observations.[10] All data sets are obtained via WRDS. We start with observations in 1987 to match the availability of a substantive part of the Dealscan and harmonised BEA productivity data.

Information on R&D expenditures is obtained from the National Science Foundation's Survey of Industry Research and Development (SIRD). Data on labor productivity comes from the Labor Productivity and Costs (LPC) tables of the Bureau of Labor Statistics (BLS).

B. Measuring Liquidation Values

Following Viral V. Acharya, Rangarajan K. Sundaram and Kose John (2011), Calomiris et al. (2015), Campello and Giambona (2013) and Campello and Larrain (2016), we define our main proxies of liquidation values by using the variables *Machinery & Equipment* (*ppenme*) and *Land & Buildings* ($ppenli + ppenb + ppenc$) from Compustat, both scaled over total assets (*at*).[11] These variable values are net of depreciation. As in all of these papers, we generate time-averages for the period 1987-1996, for which they are available, and then create the 3-digit SIC industry average.[12] This variable definition has the advantage of alleviating at least the gravest of endogeneity concerns, since liquidation values may be endogenous to loan outcomes.[13] For our estimated effects to be endogenous, firms would have to use their loans to increase their *share* of *Machinery*

[10]The algorithm links entries according to perfect matches of any pair of three variables found in both files: the company name variable, the ticker symbol and the city of headquarter location. Company and city name string variables are standardized before the file merger.

[11]We follow Chaney, Sraer and Thesmar (2012) and include "Construction in Progress" as *Land & Buildings*.

[12]The results are almost equivalent for using approximated net values based on the gross values of our proxies available over the whole time period. We prefer using averages since some sectors are only represented by a small number of firms, making medians unreliable approximations. All results are unchanged when we use sector medians (see online appendix) and defining the averages on the 4-digit SIC level (available upon request).

[13]There is evidence of firms using financing to acquire more tangible assets (Murillo Campello and Dirk Hackbarth, 2012), in line with the idea of a self-reinforcing financial accelerator (e.g. Ben S. Bernanke, Mark Gertler and Simon Gilchrist, 1999; John Geanakoplos, 2010).

& Equipment or *Land & Buildings* in total assets. We are not aware of any evidence indicating that this is a valid concern, and it seems unlikely given that a firm's real asset structure is mainly determined by the industry it operates in (Rauh and Sufi, 2011). Overall, we believe our time-invariant proxies of liquidation values are plausibly at least weakly exogenous to the loan outcomes for all practical purposes.

Our working assumption is that liquidation values matter mainly on the industry level, which is intuitive given that they are highly homogeneous within sectors (Rauh and Sufi, 2011). Indeed, it is unlikely that variations in asset structures are of any significant magnitude *within the same industry* and thus important determinants of financial contracts.[14] Graph 2 shows the nine deciles for both variables and the industries at the respective values.

To check that our results are not driven by time-averaging, we use two additional alternative measures of redeployability as robustness checks. First, we use BEA industry level data to compute the shares of *Machinery & Equipment* and of *Land & Buildings* in tangible assets (excluding intangibles). Second, we construct time-varying values by using the gross values for *Land & Buildings* ($[fatb + fatp]$) and *Machinery & Equipment* ($fate$) and depreciating them using an approximation. The exact definitions and results for these robustness exercises can be found in the online appendix.

We employ a set of alternative redeployability measures using the collateral actually specified in the loan contract from Dealscan (package $facilitysecurity$). To our knowledge, we are the first to tap into this source. We are able to match 8,842 observations to our Compustat data. For our purposes, one major drawback of this data is that there is no specific category on *Machinery & Equipment*. Instead, manually reading the extensive *comment* section of the package reveals that the group *Property & Equipment* includes both loans secured on property

[14]Note that, econometrically, this is the estimate a regression of loan terms on firm-level liquidation values would yield when using industry fixed effects, as required by the structure of our dataset.

as well as machinery and equipment. The category "Real Estate" only makes up a negligible fraction of loans. We attempt to resolve this issue by using a text search algorithm which scans the *comment* section.[15] Given the imperfect nature of the contract level data, we define two sets of variables to capture the collateral classification. For the main estimation, we code loans as either secured by *Machinery & Equipment* or *Land & Buildings* to broadly match our main liquidation value proxies. We can also observe if a loan is secured by "Cash and Marketable Securities" (more redeployable) or "Plant" (less redeployable), we assign these to *Land & Buildings* and *Machinery & Equipment*, respectively, but keep the nomenclature for clarity.[16] For robustness, we further follow Liberti and Mian (2010) and classify collateral as *specific* or *non-specific*, which yields almost equivalent results. The intuition is that specific assets are less, and non-specific assets more redeployable. The precise classifications are described in table 10.[17]

C. Loan Contract Terms

The loan contract terms we are most interested in are the loan amount ($facilityamt$); interest rate spread over a base rate, usually LIBOR ($allindrawn$); and the maturity in months ($maturity$). All of these are in natural logarithms.[18] To isolate the effect of liquidation values on loan outcomes, we hold these main contract terms constant, so we include all but the dependent variables as controls in turn as well as a dummy for whether a loan is secured or not (see below). All regressions include dummy variables for whether a firm has received a loan from the lead arranger bank before to control for an existing lender-borrower relationship; as well as for whether a loan is syndicated. We also control non-parametrically for

[15] 25 per cent of the loan facilities for the collateral type sub-sample have non-missing comments.

[16] We cannot use an equivalent classification for our balance sheet variables as a available like "Cash and Cash Equivalents" is likely to capture many different effects, including risk aversion or financial constraints.

[17] The variable definition and results for the Liberti-Mian classification are available in the online appendix.

[18] Note that our results are unchanged if we scale the loan amount over total assets instead. Results available upon request.

differences across loan purposes by including dummy variables.[19]

We attempt to test directly for the importance of claim priority by using three variables from Dealscan: a dummy variable for secured loans (*secured*); the number of financial covenants (*covenants*), ranging from 1 to 7; and a dummy for whether a loan has a borrowing base (*borrowerBase*).[20]

The collateralization of assets by definition gives lenders a senior claim in the case of bankruptcy, and thus directly allows testing for the importance of claim priority. The role of financial covenants in monitoring borrowers and enforcing creditor rights is also well documented (see e.g. Chava and Roberts, 2008). The evidence suggests that lenders use such covenants extensively to interfere with firm management decisions to maximize the likelihood of repayment (e.g. Nini, Smith and Sufi, 2009). Borrower base contracts specify one or more asset classes, usually accounts receivable or inventories, which are then used as an upper limit for how much a firm is allowed to borrow. By definition, these contracts require the bank to closely monitor the value of the specified assets. Such valuations take place regularly, often in 2 or 4 week intervals. A borrower base also protects the bank from downside risks: if a firm's financial situation deteriorates, the bank is not required to extend new or roll over existing credit. Indeed, borrower base agreements are considered senior claims with the highest average recovery rates of all debt contracts.[21] Taken together, the three variables at our disposal paint a clear picture of the seniority of a contract and the rights of a lender to interfere with firm decisions.

[19]Since we are interested in loans used for normal business transactions, we exclude all loans whose primary purpose is related to mergers and acquisition activities. These are loans whose primary purpose is identified as "Acquis. line", "LBO", "MBO", "Merger", "SBO", or "Takeover". The exclusion does not drive our results.

[20]*secured* is the prime claim priority indicator of interest and as such also included in all regressions as a control while the other two additional variables are omitted to avoid a reduction in the number of observations.

[21]See this press release and the underlying report by Moody's Investors Service for additional information.

D. Firm-level variables

To capture time-varying firm determinants of loan contracts, we include a rich set of annual control variables obtained from Compustat. We further account for potential non-linearities by including the squared and cubed values of all firm-level control variables.

Following standard procedure in the literature, we start by including book leverage, Tobin's Q, size, sales, and ROA. Size and sales are in natural logarithms. Another important control variable in our estimation is credit risk, which we attempt to capture using a dummy variable for whether a firm has any rating from Standard & Poors, Fitch, Moody's, or Duffs & Phelps. Following Roberts and Sufi (2009) and Nini, Smith and Sufi (2009), we further calculate the debt to EBITDA ratio and generate dummy variables for each quartile, as well as for negative values. We include dummy variables equal to one for the upper quartile and negative values as additional risk controls. Including numerical credit ratings significantly reduces the size of our matched sample, but all our results are unchanged if we include them (results available upon request).

Equity issuance is defined as either common shares issued times the share price, scaled over total assets; or in adjusted form using common shares issued times the share price, plus the net sale of common or preferred stock (net of share repurchases), all scaled over total assets. Dividend payouts are scaled over operating income before depreciation; retained earnings over total assets. The exact definitions can be found in table 10.

E. US Bank Branching Deregulation

The US banking system was deregulated over several decades with considerable discretion for individual states. Arguably the best documented legal changes affected restrictions on the geographical expansion across state borders (Randall S. Kroszner and Philip E. Strahan, 1999). Before 1994, most states already allowed out-of-state banks to acquire in-state competitors at least in certain cases. Out-of-state banks were also allowed to lend to local firms. However, both types of cross-border expansions were rarely practised. The limited expansion was likely linked to limited information sharing before the widespread adoption of modern telecommunication and the internet (Mitchell A. Petersen and Raghuram G. Rajan, 2002).

The passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) in 1994 lifted any remaining restrictions on bank expansion, which enabled banks to operate across borders without any state permission.[22] In particular, it allowed bank holdings to expand across state lines in four ways: (1) Interstate bank acquisitions; (2) Interstate agency operations (allowing bank subsidiaries to act as agents); (3) Interstate branching (consolidation of acquired branches into acquiring bank); and (4) De novo branching (establishment of new branch offices). Between 1994 and 2005, the number of out-of-state branches increased from 62 to 24,728 (Johnson and Rice, 2008).

However, the IBBEA allowed the individual states considerable leeway in shaping the entry of out-of-state branches. States made frequent use of these restrictions, reflecting the power struggle between the special interests of small and large banks (Johnson and Rice, 2008; Kroszner and Strahan, 2014). These political motivations are an important part of our identification strategy because they are plausibly exogenous to economic fundamentals in a given state.

Hendrickson and Nichols (2011) construct a time-varying index of the intensity of the state-level restrictions to out-of-state bank entry, ranging from 0 to 4. Their work is closely related (and in fact, equivalent for almost all state-years) to the index of Rice and Strahan (2010), but has the advantage of covering a longer period from 1992 to 2010.[23] For a more detailed description of the index and the underlying legal changes we refer the interested reader to these two papers.

[22]By 1994, eight states already permitted some form of interstate branching activity. Out of these, six allowed the entry of out-of-state branches only on a reciprocal basis. However, the US-wide ratio of out-of-state to total branches was only 0.74% in 1994. See Johnson and Rice (2008) for more details.

[23]All findings we present here are unchanged if we use the index by Rice and Strahan (2010), but it only runs until 2005. For reasons discussed in the results section, we believe it is insightful to be able to extend the sample until the post-crisis period.

The Hendrickson-Nichols index is based on the four different types of limits imposed by states opposed to foreign bank entry. They set the index to 0 for states with no restrictions and add 1 for each type of restriction imposed.[24] We use this state-level variation as an exogenous shock to the relative importance of liquidation values.

We match the index to our Dealscan-Compustat dataset using Compustat's location data (variable *state*). As described in Florian Heider and Alexander Ljungqvist (2015), this variable suffers from the flaw that it reports a firm's *current* headquarter, not the historically correct state, which introduces a measurement error. We believe that this issue is not material and indeed makes our estimates more conservative for three reasons.

First, Heider and Ljungqvist (2015) hand-collect data on firm's actual historical headquarter locations using the firms' SEC filings and find that the measurement error only affects 10.1% of all firm-years in their sample. Second, the noise introduced by the wrong headquarter locations will bias our coefficients towards 0. If a firm is incorrectly classified to be in a state which does not change its branching deregulation, the estimate will be smaller than the "true" coefficient because it effectively reduces the multiplier of the estimated coefficient (which is the liberalization index). Third, Chaney, Sraer and Thesmar (2012) use the Compustat *state* variable in a similar application, solidifying our assumption that the data quality is sound enough to yield reliable estimates.

[24]Following Hendrickson and Nichols (2011), Rice and Strahan (2010) and Favara and Imbs (2015), we set the index to "fully restricted" (0) before 1994 where we have no further information, assuming that states were fully restricted before the passage of the IBBEA. This is a reasonable approximation given the evidence on limited de facto cross-border branching activity presented above. Also note that the index assumes that the effect of liberalisation is linear across restriction levels. We tried to tease out non-linearities by creating dummy variables for each level of deregulation (0-4) but the results do not paint a clear picture, possibly owing to the discretionary nature of the index.

III. Liquidation Values, Claim Priority, and Loan Terms

A. Baseline Estimations

To test whether and how liquidation values matter for loan contracts, we use the following set-up:

$$\begin{aligned} LoanTerm_{ijst} = {} & \beta Redeployability_{i} \\ & + \gamma FirmControls_{it} + \delta ContractControls_{jt} \\ & + \alpha \mathbf{\Lambda_{kbst}} + \varepsilon_{ijst}, \end{aligned} \tag{1}$$

where i denotes firms, j a loan contract, k industries, s states, and t years.[25] $LoanTerm$ is one of the loan contract terms (loan volume, interest rate, maturity, secured, covenants, borrower base). $Redeployability$ is one of our time-invariant industry-level proxies developed above, either *Machinery & Equipment* or *Land & Buildings*. $FirmControls_{it}$ includes the firm-level control variables book leverage, Q, total assets, sales, ROA, two dummy variables for the debt-to-EBITDA ratio, and a credit rating dummy. All controls are also included in squares and cubes. $ContractControls_{jt}$ is a vector containing the remaining loan terms (loan volume, interest rate, maturity, $secured$) and loan contract controls (loan purpose, lending relationship and syndication). ε is a disturbance term.

We further stack the model with a vector of fixed effects $\mathbf{\Lambda_{kbst}}$. In its most saturated form, the vector includes dummies for $industry \times year$ (α_{kt}), $bank \times year$ (α_{bt}), and $state \times year$ (α_{st}). It is restricted in cases with fewer dummies, e.g. only industry (α_k) and year (α_t) fixed effects. These non-parametric controls are crucial to our estimation strategy, as they render the estimate of β plausibly independent of unobservable firm factors and credit demand that are not captured by the interaction term.[26] Industry fixed effects are defined using two-digit SIC

[25] As common in the literature on loan contracts, we analyse all loan contracts, even if a firm receives multiple loans from the same bank in the same year. All our results are unchanged if we define a "loan" as unique firm-bank-year pair and calculate our variables as weighted averages.

[26] As standard in the literature on loan contracts, we do not include firm fixed effects because the majority

codes. The bank fixed effects are based on the lead arranger of a loan contract, which we obtain directly from the Dealscan data. States are identified using the Compustat variable *state*, as described above. Since loan outcomes are likely to be correlated within the same firm, we cluster the standard errors by firm.[27]

It is worth emphasizing what this extensive set of non-parametric controls implies for the estimate of β. Interacting $industry$, *bank* and *state* fixed effects with *year*, we are able to account for changing conditions related to the growth opportunities and risk of specific industries; health and business model of banks; as well as legal changes and state-level economic conditions. In our most comprehensive estimation, we include 437 $industry \times year$, 332 $state \times year$, and 4,958 $bank \times year$ dummies. Note that the interactions nest simple year fixed effects to absorb changes in macroeconomic conditions and policy levers such as the stance of monetary policy.[28]

Given that the standard procedure in the literature is to include only simple firm or industry fixed effects, usually combined with year dummies, we believe that our set-up considerably raises the bar for finding any significant results. Importantly, our specification allows us to observe how loan terms differ by collateral type independent of time-varying determinants. In other words, we can estimate to which extent real asset structure matters over and beyond additional collateral that a bank may require to compensate for riskier projects or lower growth opportunities. One downside of our approach is that the combination of

of firms in the sample only have one recorded loan contract, which would diminish our sample size (see e.g. Kevin Aretz, Murillo Campello and Maria Teresa Marchica, 2015). Our main proxy variables for redeployability are further time-invariant and would thus be perfectly collinear with the firm dummies, making the estimation difficult. Apart from these practical constraints, there are also theoretical reasons not to include firm fixed effects. Due to soft information and personal relationships, changes in liquidation values may not have significant effects for loan outcomes *within the same firm* over time (which is the estimate firm fixed effects would yield). Accordingly, Joshua D. Rauh and Amir Sufi (2010) find that bank debt as a share of total capital does not rise with tangibility of a firm's assets. Instead, collateral is likely to play a much more important role in explaining differences *across firms* and industries. This is underscored by the fact that asset structures are remarkably similar within industries (Rauh and Sufi, 2011).

[27] Our results do not depend on the choice of clustering variable. All results are robust to clustering within banks or states, as well as double clustering on the firm-year, bank-year or state-year level. This is reassuring since it implies that our approach already captures the most important sources of variation in the data.

[28] Where we do not use interactions for the most basic specification, we include simple year fixed effects α_t.

extensive fixed effects and interaction terms requires an estimation of all equations using ordinary least squares. Equations where the dependent variable is a dummy (*secured* and *borrower base*) are estimated as linear probability models instead of the more common probit or logit. The obvious advantage is that the estimated coefficients have a straightforward interpretation and can be compared across specifications (also see Jiménez et al., 2014).

Table A2 shows the results of our baseline exercise for the basic loan terms, where we let our time-invariant redeployability measures on the industry level enter separately. To retain a reasonable level of clarity, we only report the results for the most parsimonious and extensive specifications, including either only simple year and industry dummies or our full set of interacted fixed effects on the industry, bank and state level.[29] Higher shares of *Machinery & Equipment* are consistently and statistically significantly associated with unfavourable loan terms. The estimated coefficients are remarkably similar across specifications, despite the saturation with the large number of interacted fixed effects in the more stringent set-up.

To assess the implied economic magnitude, it is instructive for our purposes to compare industries at the 10% and 90% percentile.[30] For *Machinery & Equipment*, these refer to the "Radio, Television, Consumer Electronics, and Music Stores" and "Wholesale Trade of Petroleum and Petroleum Products", respectively. Even in the most stringent specification, the difference in *Machinery & Equipment* between these industries is associated with 14.5% lower loan volume, 7.5% higher interest rates, and 5.4% shorter maturities. The results for *maturity* also highlight the advantage of our econometric approach. Our liquidation value proxy is more precisely estimated after shutting down unobserved

[29]Our results are robust to any specification between those extremes, available upon request.

[30]Note that assessing the economic effects using one standard deviation shifts would not be meaningful because our liquidation value proxies are heavily skewed and concentrated in values of just below 20%. A look at the distributional characteristics shows that the standard deviation of *Machinery & Equipment* (*Land & Buildings*) is only 0.11 (0.09), while the range spans 0.85 and 0.65, respectively. What we are interested in here is whether firms differing *substantially* in liquidation values, but nothing else, differ in loan terms. In fact, larger average contract differences between firms holding 21% instead of 10% of their total assets as machinery and equipment would be implausible.

state-year variation. We exploit this state-level variation in the next sections.

Reassuringly, our results are confirmed using our second proxy *Land & Buildings* in the bottom row, where the 10% and 90% percentile refer to "Computer Programming, Data Processing, and other Computer Related Services" and "Meat Products". Firms with more redeployable assets have considerably longer maturities: a 10-90 percentile difference leads to a 11.1% increase, equivalent to almost 5 months. There is also some indicative evidence that *Land & Buildings* is associated with larger facilities ($t = 1.28$), implying up to 4.6% larger loans. The coefficient for interest rates is insignificant and switches its sign between specifications, suggesting that the impact is likely zero.

To more precisely capture the channel through which liquidation values may matter for loan terms, we next estimate their effect on claim priority. In particular, we look at whether a loan is collateralized ($secured$), the number of financial covenants ($covenants$), and whether it has a borrowing base ($borrowerBase$). The results presented in table A3 are in line with banks requiring more senior claims in industries with lower asset redeployability. While the estimates for $secured$ and $covenants$ unsurprisingly lose some of their statistical power in our most stringent set-up, the coefficients do not change between specifications. If banks are uncertain about a firm's liquidation value, they are more likely to require it to pledge collateral in the contract to balance the higher perceived financial risk. For the same reasons, a higher number of financial covenants implies more intense monitoring, which is indeed what we find in the data. A 10-90 percentile increase in *Machinery & Equipment* is associated with a 2.3% higher likelihood of a loan being secured in the estimation with interacted fixed effects (not precisely estimated) or a 2.8% higher likelihood in the basic set-up. The same shift leads to 5.2% (4.1%) more financial covenants. More *Machinery & Equipment* is further clearly associated with a 4.3% higher probability of a borrower base contract (slightly less in the simple set-up). This is an important finding, given that borrowing base facilities are the debt contracts with the highest recovery rates and are usually over-collateralized. By definition, these loans are more closely monitored and classified as senior claims, both indicating that lower liquidation values induce banks to insure themselves against potential losses.

Again, our estimations for *Land & Buildings* paint a complimentary picture. More *Land & Buildings* is associated with less collateralization and a borrower base as well as fewer covenants. The difference between the liquidation values of "Computer Programming, Data Processing, and other Computer Related Services" and "Meat Products" is associated with a 3.9% decrease in the likelihood of a loan being secured (interacted set-up). While the effect on financial covenants and borrower base again is only imprecisely estimated, the coefficients are remarkably stable across specifications and mesh well with those estimated using *Machinery & Equipment*.[31] Overall, the results point to a potential nonlinearity regarding liquidation values: the detrimental effect of less redeployablility appears to outweigh the benefits from more redeployable assets in respect to loan volume, interest rate spreads, collateralization, and monitoring. The opposite is the case for the maturity.

A comparison between the industries at the very extreme ends (minimum and maximum) of the spectrum in liquidation values illustrates their substantial effect. If we take the largest estimated coefficients for *Machinery & Equipment* reported here at face value, the implied differences in loan terms between "Pipelines, except Natural Gas" (the maximum) and "Operative Builders" (the minimum) are considerable. On average, the former receives 45.2% smaller loans at 27.8% higher interest rates and 17.2% shorter maturities. The contract is further 9.5% more likely to be secured and is associated with up to 18.5% more financial covenants and 14.4% higher likelihood of a borrower base. Taking our proxy *Land & Buildings*, firms in "Social Services" (the maximum) receive

[31] In unreported regressions (available upon request), we further find that higher ratios of *Land & Buildings* are associated with a precisely estimated lower likelihood of a contract including a sweep provision, and conditional on having one, fewer sweep provisions. Sweeps are a type of covenant requiring firms to use a percentage of funds raised from asset sales, debt or equity issuance, or insurance proceeds for loan repayment. This underscores our finding that lower liquidation values are associated with a higher likelihood of banks insisting on senior claims.

15.5% larger loans and 40.5% longer maturities compared to industries holding no *Land & Buildings* such as "Rubber and Plastics Footwear". Their loans are also up to 12.6% less likely to be secured and contain 10.2% fewer covenants and 2.2% fewer borrower bases. These economic magnitudes are large, given that our liquidation value proxies are averaged over time and industry, and any information content for explaining the terms of almost 20,000 loan contracts is remarkable.[32] Even though we cannot directly compare the results, they are also in line with the elasticity in Cerqueiro, Ongena and Roszbach (2014), who find that an exogenous 13% drop in liquidation values leads to a 20 basis points increase in interest rates and 11% decrease in credit limits.

The effects on collateral and monitoring we uncover here complement the results in Cerqueiro, Ongena and Roszbach (2014), who investigate a legal reform in Sweden that exogenously reduced the liquidation values of movable assets and enabled the pledging of immovable assets in *floating lien* contracts. The positive (negative) impact of *Machinery & Equipment* (*Land & Buildings*) on the likelihood of a loan being secured we uncover here supports our model prediction that liquidation values matter not only for loan terms but also the seniority of debt claims. This adds a nuance to the argument that covenants and collateral are complements (Raghuram Rajan and Andrew Winton, 1995). While identical coefficient signs for *secured* and the two monitoring variables can be seen as support of banks using collateral and monitoring complementary, there is a crucial distinction along firms' liquidation values: more covenants and collateral are associated with *worse* loan terms in firms with lower liquidation values. This distinction suggests that lenders put significant value on the redeployability of the assets of a firm, even if they do not collateralize them explicitly in the debt contract! It is also in line with banks competing for firms with more redeployable collateral, which may result in better loan terms for these firms. We

[32] See also our discussion of economic relevance using branching regulation and state-level corporate tax increases as quasi-natural experiments below and in the online appendix.

return to this point in our investigation of the impact of branching deregulation in section IV

B. Are The Results Driven by Credit Risk or Demand Factors?

In this section, we provide evidence that all of these findings are not driven by credit risk or industry characteristics. To account for the former, our estimations contain several control variables that capture the loss given default (e.g. *secured*), the likelihood of default (e.g. ROA), or both (e.g. book leverage and industry fixed effects). The results further remain unchanged if we include numerical credit ratings for a sub-set of firms, which however reduces the sample size substantially.[33]

The included $industry \times year$ dummies ensure that the uncovered effects cannot be explained by industry-specific changes, such as shifts in input price volatility. Our results are also not driven by unobserved time-varying firm demand factors. While our data does not allow us to fully isolate a credit supply effect with firm-year effects (see e.g. Asim Ijaz Khwaja and Atif Mian, 2008; Jiménez et al., 2014), there is a strong theoretical case that our findings are not driven by unobserved credit demand. It would clearly be possible that firms in sectors with more *Land & Buildings* and less *Machinery & Equipment* have higher financing needs for technological reasons, and thus have a structurally higher demand for credit (e.g. Bolton, Chen and Wang, 2014). In order to investigate this possibility, we calculate the well-known measure of dependence on external financing by Raghuram G Rajan and Luigi Zingales (1998). They define external dependence on finance as the difference of capital expenditures and cash flow from operations, scaled by capital expenditures.[34] If this measure was positively (negatively) correlated with *Land & Buildings* (*Machinery & Equipment*), we could

[33]The tables for the baseline regressions with credit ratings are available in the online appendix.

[34]We follow their procedure and calculate the measure using Compustat data as $External\,Dependence = (CapEx - CF\,from\,Operations)/CapEx$. $CapEx$ is Compustat item # 128 and $CF\,from\,Operations$ the sum of items # 110, 123, 125, 126, 106, 213, and 217. We average the values over time, and take the sector median as in their paper (based on 3-digit SIC codes).

not reject that our results are driven by differences in credit demand.

As it turns out, the opposite is the case. The Rajan-Zingales index has a *positive* correlation with our measure of *Machinery & Equipment* (0.29) and a low *negative* correlation with *Land & Buildings* (-0.04).[35] Thus, it seems extremely unlikely that our results are driven by sector characteristics related to credit demand. If anything, they indicate that firms with structurally higher financing needs receive credit on worse conditions. Firms with lower liquidation values further do not only receive less credit, but also at more unfavourable terms. To explain these findings from a demand perspective, lenders would have to face higher costs in certain sectors independent of liquidation values, for example arising from a lack of historical data or a change in business models. Such time-varying determinants on the bank-year level, however, are comfortably controlled for by our $bank \times year$ dummies.

In the online appendix, we report the results for three additional exercises which underscore the robustness of our findings. First, we conduct a natural experiment by using the staggered state-level corporate tax increases identified by Heider and Ljungqvist (2015) as an exogenous shock to credit demand. The difference-in-difference approach we employ isolates a specific type of time-varying firm demand shock, and the results strongly supports our claim that unobserved firm factors are not a crucial confounding element. Second, we address a potential concern that the time-invariant nature of our liquidation value proxies or the sample selection may drive the results. We replace the proxies with annual, comprehensive data retrieved from the BEA and re-run our equation 1. The results are very similar (see online appendix). Third, we also replicate our findings using standard capital structure regressions with firm fixed effects: firms with more *Land & Buildings* have higher book and market leverage and a higher share of long-term debt, similar to the results in Campello and Giambona (2013).

[35] Both correlations are significant at the 1% level.

C. Are The Results Driven by Other Industry Characteristics?

One potential downside of our main explanatory variables is that they made be correlated with other unobserved industry characteristics. In this section, we verify that our baseline results are indeed driven by the type of collateral used in the loan contract. In contrast to the majority of the literature, we are able to test this directly for a broad section of firms listed in Compustat, using a hitherto untapped part of the Dealscan database. This exercise enables us to distinguish between the impact of liquidation values and claim priority, given that we only examine a sub-set of collateralized loans, which are by definition all senior claims.

The estimation is augmented accordingly by replacing our measures of $Redeployability_i$ with $Collateral_{ijt}$, which is the type of collateral actually specified in the loan contract j. This yields the augmented specification:

$$
\begin{aligned}
LoanTerm_{ijst} = {} & \beta Collateral\,Type_{ijt} \\
& + \gamma Firm\,Controls_{it} + \delta Contract\,Controls_{jt} \\
& + \alpha \mathbf{\Lambda_{kbst}} + \varepsilon_{ijst},
\end{aligned} \tag{2}
$$

where all other variables are equivalent to equation 1 above. Since all loans in this sub-sample are secured, we exclude the *secured* dummy. Standard errors are again clustered at the firm level.

Table 4 shows the results using the classification into *Machinery & Equipment* and *Land & Buildings*, adjusted to include the categories "Plant" and "Cash and Marketable Securities", respectively.[36] It is clear that the smaller sub-sample and noisy data clearly take a toll on the statistical power, but the main results also hold with our contract-level data. Loans secured with *Land & Buildings* receive larger loans at lower interest rates. The coefficient for the maturity is posi-

[36] The robustness exercises using the classification into specific and non-specific assets as in Liberti and Mian (2010) can be found in the online appendix. The results are almost identical.

tive but not statistically significant, marginally missing the 10% threshold. The estimates for *Machinery & Equipment* assets clearly lack precision, but reassuringly, all coefficients have the expected signs. Our estimate of for maturity is the exception, where the introduction of our (admittedly very stringent) fixed effects pushes the coefficient above 0, which is however not imprecisely estimated.

The role of monitoring is harder to tease out, as the sample size decreases even more. The changing signs of the coefficients for financial covenants suggest that the results are likely to be zero, which implies that conditional on a loan being collateralized, liquidation values do not play an additional role for covenants. Collateralization with *Machinery & Equipment*, however, is still clearly associated with borrower base contracts. This finding also holds for *Land & Buildings*, which attracts the opposite coefficient in both specifications.

Our estimates imply that facilities secured *Land & Building* are on average 7.6 to 8.2% larger; have 3.3 to 3.7% lower interest rates; and 2.2 to 3.7% longer maturities. Loans secured by *Machinery & Equipment* in turn are 3.3% more likely to have a borrowing base. These results mesh well with the estimates from the sector-level data and show that liquidation values matter over and above claim priority. The effect of monitoring remains somewhat unclear, because liquidation values are still associated with borrower base contracts but not the number of financial covenants. We cannot fully exclude the possibility that the smaller sample size for financial covenants drives our results.

IV. Bank Branching Deregulation as a Quasi-Natural Experiment

In the previous sections we have established that the liquidation values of firms have substantial impact on their loan terms. Our simple model further predicts that an exogenous shock to the importance of liquidation values would help to isolate the effect empirically. We argue that the entry of out-of-state banks during the bank branching deregulation in the US constitutes such a quasi-natural experiment by increasing the costs of monitoring borrowers compared to requiring more collateral. The lifting of branching restrictions may have increased the relative importance of collateral through three channels: lender characteristics; competition; and collateral values.

Lender characteristics. After the passage of the IBBEA, bank holdings were able to enter new markets in other states about which they possessed little historical information, both hard (e.g. average default rates) and soft (e.g. through personal relationships). The immediate impact of the state-level reforms thus introduced an increase in monitoring costs for out-of-state lenders. Since banks expanding across state borders are also likely to be larger, the average bank size may have increased following branching deregulation. Larger banks in turn tend to rely more on transaction-based hard information such as ratings and collateral than on soft information (Allen N. Berger, Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan and Jeremy C. Stein, 2005). Further, the distance between lenders (the bank headquarters) and borrowers increased. Physical proximity plays an important role for loan outcomes through its impact on the acquisition of soft information (e.g. Robert DeYoung, Dennis Glennon and Peter Nigro, 2008; Sumit Agarwal and Robert Hauswald, 2010). In particular, firms with lower liquidation values are more informationally opaque to the lender due to their more uncertain liquidation values, making them more dependent on monitoring. As the distance to the borrower increases, banks are likely to rely on collateral to bridge increasing informational asymmetries. Larger distances between branches and headquarters may also lead to decreased efficiency within the same bank (Allen Berger and Robert DeYoung, 2001).

Competition. In the case of the lifting of state-level branching restrictions, both local and out-of-state lenders came under considerable pressure to defend and gain market share, respectively. While this had well-documented benefits for credit availability and cost, it may also have shifted banks' focus from monitoring to collateral, as in Robert Marquez (2002) and Hauswald and Marquez (2006). This also meshes with the finding that ex-ante risk taking increases during credit expansions, arguably due to less stringent screening (Jiménez et al., 2014). Since firms with lower liquidation values are likely to rely more on lenders using soft information, increased competition may also harm them through its impact on relationship formation (Mitchell A Petersen and Raghuram G Rajan, 1995).

Collateral values. Bank branching deregulation was followed by strong increases in house prices and mortgage credit (Favara and Imbs, 2015). Where residential and commercial house prices move together, deregulation increased the liquidation values of firms holding more land and buildings on their balance sheets (Chaney, Sraer and Thesmar, 2012).

To gauge how the role of asset redeployability changed with the state-wise lifting of branching restrictions, we use a specification similar to Calomiris et al. (2015), Campello and Larrain (2016), and Favara and Imbs (2015):

$$\begin{aligned} LoanTerm_{ijst} = {} & \beta_1 D_{st} + \beta_2 D_{st} \times Redeployability_i \\ & + \gamma FirmControls_{it} + \delta ContractControls_{jt} \\ & + \alpha \mathbf{\Lambda_{kbst}} + \varepsilon_{ijst}, \end{aligned} \tag{4}$$

where D_{st} denotes the index of branching deregulation and all other variables are unchanged to the baseline equations above.[37] i continues to index firms, k industries, b banks, s states, and t years. Our main coefficient of interest β_2 yields an estimate of how the importance of redeployability has changed with bank branching deregulation.[38] Since the state-level deregulation is plausibly exogenous to any contract-level outcome, the approach is akin to a difference-in-difference set-up. Note that the estimation period now only runs until 2008, which is the last year for which Hendrickson and Nichols (2011) calculate their

[37] Note that D_{st} is nested within the $state \times year$ fixed effects specification reported here.

[38] We are making the assumption that headquarter location matters for the choice of lenders in our sample. Motivated by the results in Chaney, Sraer and Thesmar (2012), who find that local house prices matter for financing constraints using Compustat data, we see this as an additional hurdle for identifying any effect of redeployability. Given the noise introduced by the likely measurement error and the large firm size in our sample, the results are again a lower bound for the importance of redeployability on the average US firm.

index. The results becoming even stronger if we assume no changes after 2008 and estimate the equation until the end of our sample. We discuss this issue below.

Table 6 shows the results using our industry-level variables, which lend considerable support to the hypothesis that the importance of liquidation values for loan contract terms has increased with branching deregulation. The interaction of D_{st} with *Machinery & Equipment* is highly significant for all regressions except *secured* and *covenants*, indicating that the lifting of branching restrictions has indeed negatively impacted industries with lower liquidation values. This is complemented by the opposite signs for *Land & Buildings*, where all estimations except that for borrower base contracts are statistically significant. The three insignificant estimates also attract the expected signs, and become significant if we use only industry and year fixed effects (unreported). Extending the sample period to 2014, all of these estimates are much more precisely estimated, which points to the decreased sample size excessively pushing up the standard errors.[39] In any case, all coefficients imply that in states with fewer restrictions, higher liquidation values are also associated with fewer financial covenants and borrower base contracts.

To put the estimated coefficients into perspective, consider a firm holding 19% of its assets as *Machinery & Equipment*, which is equal to the sample mean. In a state lifting all branching restrictions, i.e. moving from 0 to 4 on our index D, the firm receives 21% smaller loans, 7% higher interest rates, and almost 6% shorter maturities only due to its liquidation values.[40] Similarly, the firm's loans are 3.4% more likely to be secured, 3.8% to have a borrowing base, and have on average 3.5% more financial covenants; however, only the borrower base regression yields a coefficient significant at the 10% threshold. Considering the *Land & Building* proxy, when kept at its mean of 13%, branching deregulation increased

[39]These full estimations are available on request.

[40]To see this, consider for example the calculation for the impact on the loan volume, which is $EXP(-0.304 * 4 * 0.19) - 1 = -0.206$.

the maturity of the loan by 8.4% through liquidation values. The likelihood of a loan to be secured decreased by 5.5%, and the number of financial covenants by 4.4%.

These effects become much more pronounced when we consider firms holding larger fractions of their assets in *Machinery & Equipment* or *Land & Buildings*, for example the 90% percentiles equal to 34% and 24%, respectively. Taking the largest estimated coefficients at face value, the results imply that branching deregulation changed these firms' loan terms by -33.9% or $75,000,000 for loan volume (*M&E*); +12.7% or 30 basis points for the interest rate spread (*M&E*); +16% or 7 months for maturity (*L&B*); -10.1% (*L&B*) and +5% (*M&E*) for their likelihood of being secured or tied to a borrower base, respectively; and -8% fewer covenants (*L&B*). These estimates suggest that the lifting of branching restrictions has amplified frictions arising from sectoral differences in liquidation values. The benefits of deregulation have disproportionally fallen on sectors with higher liquidation values.

At this point, the positive, significant ($t = 2.18$) coefficient for the regression of *interest* on *Land & Buildings* in column 4 demands attention, which is indeed higher than that for *Machinery & Equipment*. While uncaptured geographic factors correlated with branching deregulation could be the driving force behind this positive estimate, it is still worth exploring alternative explanations. Robert Marquez and M. Deniz Yavuz (2013) set up a model of endogenous asset specifity with two opposing effects on financial contracts. On one hand, more specific assets have lower liquidation values, with the expected effects we have documented throughout this paper. On the other hand, asset specifity increases a firm's productivity and incentive to repay, which again should lead to more favourable contract terms. If firms with specific assets are able to convince lenders of their repayment commitment, their lower liquidation values may not pose a disadvantage in loan contracts, leading to the lack of a difference between the coefficient signs for *Machinery & Equipment* and *Land & Buildings* we find here.

Another, simpler explanation is the rapid growth in mortgages and house prices in the states deregulating bank branching restrictions (Favara and Imbs, 2015). Increases in the price of housing spur capital expenditures and the purchase of real estate for investment purposes, especially for sectors with structurally high levels of land and buildings (Chaney, Sraer and Thesmar, 2012; Campello and Hackbarth, 2012). If the resulting credit demand of firms in these industries outpaces credit supply, the expected general equilibrium outcome would be an increase in interest rates for these sectors, exactly what we are observing in the data. We believe that there is considerable merit to this hypothesis, given that our estimation period spans from 1987 to 2008, a period over which the S&P/Case-Shiller U.S. National Home Price Index grew by a factor of 2.48.[41] Indeed, in the regression of *interest* on *Land & Buildings*, the coefficient becomes considerably smaller and loses some statistical significance if we estimate it over the whole sample period until 2014. In these unreported regressions, the point estimate of *Machinery & Equipment* changes little and always stays positive and highly significant. Since national house prices took a considerable dive during the Great Recession, and are still to return to their peak in 2006 at the time of writing, this lends some evidence to the idea that the somewhat counter-intuitive interest rate sign may due to credit demand outstripping supply in sectors with structurally high land holdings during branching deregulation.

Overall, our results suggest that bank branching deregulation may have increased banks' reliance on redeployable collateral. The benefits of fewer restrictions appear to have disproportionally benefited firms in sectors with structurally higher liquidation values. These findings add an additional, cautionary dimension to the well-established findings on the benefits of bank branching deregulation (e.g. Kroszner and Strahan, 2014). The accompanying increasing

[41] Based on the yearly average of the index.

role of transaction-based banking may have come at the expense of industries with less redeployable assets.

It is worth noting that what we document here is likely an extreme lower bound. As we show in section II, using the Compustat variable *state* to identify firm location significantly biases our estimates towards zero. Given the nature of our data set, we also only look at large public firms, which potentially have other means of raising capital. The effects are likely to be much more pronounced for smaller firms.

V. Macroeconomic Implications

Until this point of the article, we have documented that liquidation values across industries matter significantly for loan contract terms, and that they have become more important with bank branching deregulation. But what macroeconomic relevance does this have, if any? In this section, we document three stylized facts which may serve as guidance on these questions for future research.

First, firms in sectors with lower liquidation values do not make up for the disadvantage in credit markets by issuing equity or using internal cash flows. The possibility that this might be the case goes back at least to the argument of Williamson (1988) that projects with less redeployable assets should be financed with equity. We run a simple test by regressing two variables for equity issuance on our baseline liquidation value proxies and the full set of firm control variables and fixed effects from the specifications above. The results in table 7 indicate that firms with lower liquidation values indeed also raise *less* equity and pay out *more* earnings as dividends while firms with higher liquidation values have *more* retained earnings.[42]

Second, liquidation values are negatively correlated with productivity growth.

[42]It could theoretically be possible that the shortfall in financing is made up from other sources such as bond finance, leasing or supplier credit. However, we doubt that leasing or supplier credit are likely to make up for the entire shortfall in the US credit market. While bond financing would be interesting to analyze, Dealscan is not a comprehensive data set of all bank loans, so observed changes in firm leverage may also stem from loans not covered in the database. Further, bonds are just another type of debt contract, often also held by banks, so it is unclear why the frictions uncovered here should not be present.

In particular, our main proxies for *Machinery & Equipment* and *Land & Buildings* have a correlation of 0% and -26% with average sectoral productivity growth over our sample period, respectively.[43] For the time-varying BEA measure *Equipment*, the value is 10.8%.[44] A look at the left half of figure 3 is even more instructive, where productivity growth is clustered into above and below average sectors for both of our main liquidation value proxies. Average annual productivity growth is 3.8 percentage points lower for firms holding more *Land & Buildings*, and 0.6 percentage points higher for firms holding more *Machinery & Equipment* (the difference is significant, $t = -15.56$). Looking at the share of *Machinery & Equipment* in the sum of both yields an even sharper picture: the difference in average productivity growth between the groups is almost 5.3 percentage points! The firms with the highest liquidation values, who likely receive the best loan terms according to our estimations, have the lowest average productivity growth by a significant margin. These findings add empirical evidence to the predictions of Marquez and Yavuz (2013) that firms with more specific assets are more productive and may be able to secure superior loan terms if they are able to convince lenders of their repayment commitment. At least on the sectoral level, higher productivity has adverse consequences on loan contract terms due to its negative correlation with liquidation values.

The pattern we uncover here is not merely suggestive, but also holds if we replace the liquidation value proxies in our baseline estimation 1 with average sectoral productivity growth. Strikingly, table 8 shows that the estimated coefficients are highly significant and take the same signs as *Machinery & Equipment*, except for the *Covenants* variable which is insignificant. This holds both when using time averages and the annual sectoral productivity growth, implying that firms in sectors with higher average productivity receive fewer loans at worse

[43]To make the measures comparable with our main proxies, we take the time-average of the BEA productivity data. The value for *Land & Buildings* is statistically significant at the 1% level.

[44]Since both *Equipment* and *Structures* are scaled over total tangible assets, the correlation for the latter is -10.8%, accordingly. These are significant at the 1% level.

contract terms and are more stringently monitored.[45] These findings are all the more impressive given that productivity growth is clearly endogenous: firms in industries receiving better loan contracts could have used the additional capital to invest in productivity-enhancing activities. The observed visual differences presented in figure 3 and the estimated coefficients in table 8 thus *downplay* the negative correlation between productivity and loan terms.

Third, this finding is substantiated by a comparison of our asset redeployability measures with data on innovation activity. The right half of figure 3 clusters average R&D expenditures (scaled by total sales) obtained from the BEA into above and average clusters, akin to productivity above. For both liquidation value proxies, R&D expenditures are higher for *below* average shares. These findings are driven by the strong correlation of intangibles with R&D activity. However, the gap is significantly wider for *Land & Buildings* (3.8 percentage points compared to 3.2 percentage points), implying that sectors holding more redeployable assets are less innovative. The third set of bars in the table divides the sample according to whether industries are below or above the share of *Machinery & Equipment* in the sum of (*Machinery & Equipment* and *Land & Buildings*). Abstracting from the impact of intangibles, industries which employ more *Machinery & Equipment* and thus have lower liquidation values engage in about 2.1 percentage points or 50% more R&D activity.

Next, we replace the main proxies in our baseline regressions with measures of R&D expenditure, akin to the productivity exercise above. The results in table 9 again underscore that firms in sectors with higher R&D expenditure receive smaller loans at inferior terms.[46] This may be one explanation for the negative link between productivity growth and loan contract terms. Note that for the regression results and figure 3 there is, again, a highly likely downward bias

[45]The coefficients for the time-varying productivity growth variable are slightly smaller but still highly significant. Available on request.

[46]We also used other measures of innovative activity, such as the number of patents issued or R&D over total assets. The results are very similar and are available upon request.

due to the endogeneity of R&D expenditures. Companies with high shares of *Machinery & Equipment* may have even higher R&D expenditures if they had better access to credit markets.

While we refrain from making strong claims about causal inference at this point, these findings have potentially important implications. If banks favour lending to sectors with higher liquidation values but lower productivity growth and innovative activity, this may well have consequences for industry structure and the macroeconomy.[47] This seems especially likely when even the large, publicly traded firms we are studying here do not compensate with internal cash flows or by raising more equity. In the language of an important paper by Kiminori Matsuyama (2007), our results are consistent with a *credit trap* regime, characterised by low productivity growth in steady state. Our paper thus also adds evidence to recent debates on the efficiency of capital allocation and the determinants of productivity growth slowdown (e.g. Stephen G Cecchetti and Enisse Kharroubi, 2015; Lawrence H. Summers, 2015).

VI. Conclusion

It is well known that collateral plays an important part in financial contracting. In this paper, we take a step forward by showing that liquidation values in particular play an important role in shaping loan terms, even in a credit market with abundant information sharing and flexible collateral laws such as the US. We also show that the arising frictions – lower loan volume and inferior terms – cannot be compensated for by using claim priority as a contractual device. Using a range of exercises, and drawing on the popular Rajan-Zingales measure, we show that these findings are unlikely to be driven by credit demand and unobserved firm-specific factors. Since firms with less redeployable assets do not make up for their disadvantage in credit markets by issuing equity, we believe

[47] Our findings are not driven by the financial crisis 2007-08 or recessions. We verify this by interacting our productivity and R&D variables with a dummy variable of whether the loan was issued during an NBER recession, which yields no clear pattern. Results available upon request.

it is unlikely they are able to fully compensate by tapping other sources of financing, such as the bond market or trade credit. Due to data limitations for our sample of firms, this remains subject to further inquiry.

Our findings have important macroeconomic implications because of the clear negative relationship of productivity growth and innovation with liquidation values, even when controlling stringently for other unobserved factors. While the staggering costs of financial crises are now almost universally acknowledged, our findings indicate that the inability to contract around liquidation values leads to substantial frictions in the efficient capital allocations by the banking system *even in normal times* (Cecchetti and Kharroubi, 2015). We further provide evidence that these frictions have become larger with bank branching deregulation. Our results thus also speak to the reinvigorated debate on the merits and drawbacks of relationship-based and transaction banking (e.g. Patrick Bolton, Xavier Freixas, Leonardo Gambacorta and Paolo Emilio Mistrulli, 2013; Thorsten Beck, Ralph de Haas, Hans Degryse and Neeltje Van Horen, 2014).

Due to the stringent fixed effects specifications and the use of data on large firms with publicly traded stocks and easy access to the bond market, the uncovered effects can only be considered a lower bound. Liquidation values are likely to play a considerably greater role for smaller, more opaque firms. An even greater amplification of the effects found is likely to be present in countries with less flexible collateral laws, creditor rights, information sharing, and financial markets that are generally not as developed as in the US (see Kee-Hong Bae and Vidhan K. Goyal, 2009). Future research should address these important issues.

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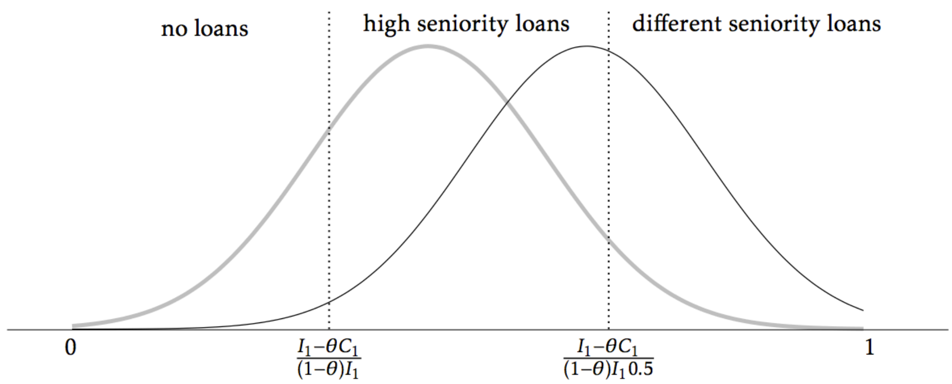
Figure 1: Loan Supply and Seniority Vary with Liquidation Values



The thick gray curve represents the distribution of low liquidation values for an example industry with more M&E (e.g. biotechnology), the thin black curve is an example industry with more L&B (e.g. department stores). The dotted vertical lines represent the threshold values for liquidation values below which no loans (left section of the graph) and only high seniority loans (middle section) are offered. In the right section both low and high seniority loans are offered.

Table 1: Descriptive Statistics

	mean	median	SD	p10	p25	p75	p90	Obs.
Main explanatory variables								
M&E	0.19	0.16	0.11	0.09	0.14	0.22	0.34	18,965
L&B	0.13	0.11	0.09	0.04	0.07	0.15	0.24	18,965
Alternative explanatory variables								
$M\&E_{sec}$	0.09	0.00	0.29	0.00	0.00	0.00	0.00	7,945
$L\&B_{sec}$	0.08	0.00	0.28	0.00	0.00	0.00	0.00	7,945
Productivity	0.05	0.03	0.10	-0.04	0.00	0.07	0.15	15,325
RD	0.05	0.03	0.05	0.01	0.01	0.06	0.12	5,218
Loan Conditions								
loan volume	222.60	65.00	584.26	4.00	15.00	225.00	500.00	18,965
interest rate	230.40	225.00	147.02	62.50	125.00	300.00	405.00	18,965
maturity	44.08	42.00	24.08	12.00	24.00	60.00	72.00	18,965
secured	0.76	1.00	0.42	0.00	1.00	1.00	1.00	18,965
covenants	0.78	0.69	0.45	0.00	0.69	1.10	1.39	12,544
bbase	0.16	0.00	0.37	0.00	0.00	0.00	1.00	18,965
Contract controls								
syndicated	0.49	0.00	0.50	0.00	0.00	1.00	1.00	18,965
relation	0.36	0.00	0.48	0.00	0.00	1.00	1.00	18,965
Firm controls								
leverage	0.34	0.31	0.26	0.04	0.16	0.47	0.64	18,965
Q	1.38	1.09	1.05	0.57	0.77	1.62	2.48	18,965
at	2,764	402	13,388	34	99	1,586	5,077	18,965
sales	2,510	426	9,312	38	113	1,550	4,977	18,965
ROA	0.11	0.12	0.19	0.00	0.07	0.17	0.23	18,965
$Debt/EBITDA_{q4}$	0.38	0.00	0.49	0.00	0.00	1.00	1.00	18,965
$Debt/EBITDA_{neg}$	0.06	0.00	0.23	0.00	0.00	0.00	0.00	18,965
rating	0.40	0.00	0.49	0.00	0.00	1.00	1.00	18,965

This table summarizes all variables used. The sample covers the observations in equation 1 of table 1. Variables come from Compustat, Dealscan and BEA sources. *at*, *sale*, and *loan volume* are in millions of $, *interest rate* is in basis points and *maturity* in month. These variables are in logarithms in the regressions. p10, p25, p75, and p90 are the 10, 25, 75, and 90 percentiles.

Figure 2: Shares of Asset Types in % of Total Assets, Decentiles

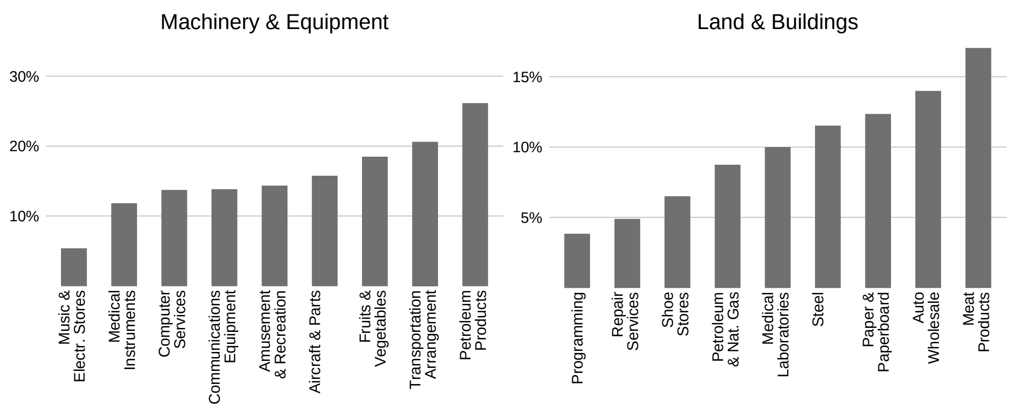


Figure 2 shows the share of *Machinery & Equipment* and *Land & Buildings* in total assets for those industries that lie at the decentile points of the distribution of each variable.

Figure 3: Productivity and R&D Expenditures by Liquidation Values

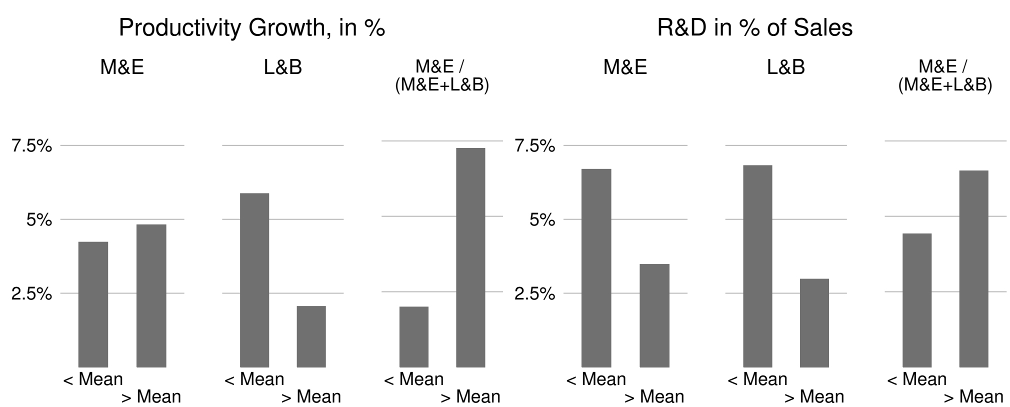


Figure 3 shows average productivity growth and R&D expenditures, clustered by liquidation values. The left figure shows average growth rates in labor productivity from 1987 to 2014. The right shows average R&D expenditures, scaled by total sales. The values are divided into below or above the average values of $M\&E$ (bars 1 and 2) and $L\&B$ (bars 3 and 4). Bars 5 and 6 divide the sample into above or below the average share of $M\&E$ in the total of $M\&E + L\&B$.

Table 2: THE EFFECT OF LIQUIDATION VALUES ON LOAN TERMS

	loan volume				*interest rate*				*maturity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
M&E	-0.713***	-0.628***			0.246***	0.290***			-0.088	-0.224**		
	(0.154)	(0.146)			(0.074)	(0.086)			(0.079)	(0.094)		
L&B			0.009	0.223			-0.030	0.085			0.218**	0.525***
			(0.202)	(0.174)			(0.109)	(0.119)			(0.109)	(0.130)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	18,965	16,660	18,965	16,660	18,965	16,660	18,965	16,660	18,965	16,660	18,965	16,660
R^2	0.796	0.867	0.795	0.866	0.622	0.791	0.622	0.791	0.311	0.545	0.311	0.545

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. The contract terms *loan volume*, *interest rate* and *maturity*, and *secured* are included as controls. The same is the case for regular and interactive fixed effects (of year, industry and state) as well as contract and firm level control variables. "Higher order" includes squared and cubed values of all firm controls. *secured* is a dummy variable for the loan being secured (1) or not (0). Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table 3: The Effect of Liquidation Values on Claim Priority

	secured				*covenant*				*bbase*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
M&E	0.112**	0.090			0.201***	0.161*			0.165***	0.170***		
	(0.053)	(0.069)			(0.073)	(0.087)			(0.042)	(0.051)		
L&B			-0.085	-0.194**			-0.173	-0.166			-0.021	-0.034
			(0.073)	(0.087)			(0.114)	(0.120)			(0.056)	(0.072)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	18,965	16,660	18,965	16,660	12,541	11,129	12,541	11,129	18,965	16,660	18,965	16,660
R^2	0.446	0.651	0.446	0.651	0.251	0.596	0.250	0.595	0.250	0.471	0.249	0.471

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. *secured* is a dummy variable for the loan being secured (1) or not (0). *covenant* is the number of financial covenants in the loan contract, *bbase* is a dummy indicating the if the loan contract contains a borrower base arrangement (1) or not (0). The contract terms *loan volume*, *interest rate* and *maturity*, and *secured* are included as controls. The same is the case for regular and interactive fixed effects (of year, industry and state) as well as contract and firm level control variables. "Higher order" includes squared and cubed values of all firm controls. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table 4: Pledged Security Type and Loan Terms

	loan volume				*interest rate*				*maturity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
$M\&E_{sec}$	-0.069*	-0.059			0.029	0.022			-0.013	0.006		
	(0.040)	(0.052)			(0.022)	(0.024)			(0.029)	(0.036)		
$L\&B_{sec}$			0.073**	0.079*			-0.038*	-0.034			0.036	0.022
			(0.037)	(0.046)			(0.023)	(0.027)			(0.022)	(0.029)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	8,001	7,041	8,001	7,041	8,001	7,041	8,001	7,041	8,001	7,041	8,001	7,041
R^2	0.742	0.838	0.742	0.838	0.369	0.708	0.369	0.708	0.375	0.633	0.375	0.633

The columns of this table lists regressions of loan terms on *Machinery & Equipment* and *Land & Buildings*. $M\&E_{sec}$ and $L\&B_{sec}$ are 1 if the security behind the loan is classified as machinery and equipment or plant and as land and buildings or cash and marketable securities respectively (they are 0 otherwise). The contract terms *loan volume*, *interest rate* and *maturity*, and *secured* are included as controls. The same is the case for regular and interactive fixed effects (of year, industry and state) as well as contract and firm level control variables. "Higher order" includes squared and cubed values of all firm controls. *secured* is a dummy variable for the loan being secured (1) or not (0). Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table 5: Pledged Security Type and Claim Priority

	covenants				*bbase*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Liquidation Value Proxies								
$M\&E_{sec}$	0.007	-0.027			0.032*	0.024		
	(0.024)	(0.030)			(0.018)	(0.026)		
$L\&B_{sec}$			0.015	-0.028			-0.006	-0.015
			(0.021)	(0.027)			(0.014)	(0.021)
Controls								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Year	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	6,628	5,826	6,628	5,826	8,001	7,041	8,001	7,041
R^2	0.241	0.679	0.241	0.679	0.268	0.521	0.268	0.521

The columns of this table lists regressions of loan terms on *Machinery & Equipment* and *Land & Buildings*. *M&E_sec* and *L&B_sec* are 1 if the security behind the loan is classified as machinery and equipment or plant and as land and buildings or cash and marketable securities respectively (they are 0 otherwise). *secured* is a dummy variable for the loan being secured (1) or not (0). *covenant* is the number of financial covenants in the loan contract, *bbase* is a dummy indicating the if the loan contract contains a borrower base arrangement (1) or not (0). The contract terms *loan volume*, *interest rate* and *maturity*, and *secured* are included as controls. The same is the case for regular and interactive fixed effects (of year, industry and state) as well as contract and firm level control variables. "Higher order" includes squared and cubed values of all firm controls. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table 6: State-Level Bank Branching Deregulation as a Quasi-Natural Experiment

	loan volume		*interest rate*		*maturity*		*secured*		*covenants*		*bbase*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
$M\&E \times lib$	-0.304***		0.088**		-0.077*		0.045		0.045		0.050*	
	(0.061)		(0.041)		(0.041)		(0.031)		(0.036)		(0.026)	
$L\&B \times lib$		0.178**		0.109**		0.155***		-0.105***		-0.087*		-0.016
		(0.083)		(0.050)		(0.057)		(0.041)		(0.050)		(0.035)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	-	-	-	-	-	-	-	-	-	-	-	-
Industry	-	-	-	-	-	-	-	-	-	-	-	-
Industry*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13,254	13,254	13,254	13,254	13,254	13,254	13,254	13,254	8,933	8,933	13,254	13,254
R^2	0.872	0.872	0.799	0.799	0.546	0.546	0.669	0.669	0.600	0.601	0.481	0.481

The columns of this table lists regressions of loan terms on *Machinery & Equipment* ($M\&E$) and *Land & Buildings* ($L\&B$). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. $M\&E \times lib$ and $L\&B \times lib$ are interaction effects of $M\&E$ and $L\&B$ with an index for bank deregulation which has values between 0 and 4 (higher numbers indicate more deregulation). *secured* is a dummy variable for the loan being secured (1) or not (0). *covenant* is the number of financial covenants in the loan contract, *bbase* is a dummy indicating the if the loan contract contains a borrower base arrangement (1) or not (0). The contract terms *loan volume*, *interest rate*, *maturity*, and *secured* are included as controls. The same is the case for interactive fixed effects (of year, industry and state) as well as contract and firm level control variables. "Higher order" includes squared and cubed values of all firm controls. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table 7: The Effect of Liquidation Values on Equity and Internal Finance

	equity issuance		*new equity*		*retained earnings*		*dividend payout*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M&E	-0.119***		-0.070**		0.525		0.406**	
	(0.028)		(0.030)		(0.363)		(0.160)	
L&B		0.014		0.015		1.751***		-0.107
		(0.046)		(0.048)		(0.552)		(0.156)
Fixed Effects								
Year	-	-	-	-	-	-	-	-
Industry	-	-	-	-	-	-	-	-
Industry*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	72,256	72,256	65,028	65,028	120,372	120,372	121,712	121,712
R^2	0.978	0.978	0.964	0.964	0.387	0.387	0.025	0.025

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. *new issuance* is the value of equity issued and *new equity* the value of equity issued plus existing equity sold minus stock repurchases. *Retained earnings* are scaled over total assets. Total dividend payouts are expressed in % of total operating income before depreciation. Regular and interactive fixed effects for year, industry and state are included. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table 8: Average Annual Labor Productivity Growth as Explanatory Variable

	loan volume		*interest rate*		*maturity*		*secured*		*covenants*		*bbase*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
Productivity	-0.013***	-0.005*	0.008***	0.004**	-0.004**	-0.002	0.003***	0.004***	-0.003	0.001	0.002**	0.002
	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	15,453	13,468	15,453	13,468	15,453	13,468	15,453	13,468	10,203	8,983	15,453	13,468
R^2	0.801	0.873	0.634	0.809	0.315	0.565	0.463	0.683	0.258	0.629	0.254	0.494

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. *Productivity* is the average industry level annual percentage change in labor productivity for 1987-2014. *secured* is a dummy variable for the loan being secured (1) or not (0). *covenant* is the number of financial covenants in the loan contract, *bbase* is a dummy indicating the if the loan contract contains a borrower base arrangement (1) or not (0). The contract terms *loan volume*, *interest rate*, *maturity*, and *secured* are included as controls. The same is the case for regular and interactive fixed effects (of year, industry and state) as well as contract and firm level control variables. "Higher order" includes squared and cubed values of all firm controls. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table 9: Average R&D Expenditures as Explanatory Variable

	loan volume		*interest rate*		*maturity*		*secured*		*covenants*		*bbase*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
R&D	-1.164***	-0.844***	0.290*	0.405**	-0.327*	-0.243	0.005	0.113	-0.393**	-0.088	0.107	0.014
	(0.251)	(0.275)	(0.161)	(0.184)	(0.192)	(0.213)	(0.114)	(0.141)	(0.167)	(0.183)	(0.096)	(0.120)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	17,515	15,296	17,515	15,296	17,515	15,296	17,515	15,296	11,672	10,314	17,515	15,296
R^2	0.797	0.870	0.620	0.795	0.309	0.551	0.445	0.661	0.243	0.602	0.249	0.475

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. *R&D* is the average industry level R&D expenditure for 1987-2014. *secured* is a dummy variable for the loan being secured (1) or not (0). *covenant* is the number of financial covenants in the loan contract, *bbase* is a dummy indicating the if the loan contract contains a borrower base arrangement (1) or not (0). The contract terms *loan volume*, *interest rate*, *maturity*, and *secured* are included as controls. The same is the case for regular and interactive fixed effects (of year, industry and state) as well as contract and firm level control variables. "Higher order" includes squared and cubed values of all firm controls. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table 10: Vairable Descriptions

Variable	Definition
Firm-Level Variables (Compustat)	
M&E	Machinery & equipment (*ppenme*) / total assets (*at*). Values are net of depreciation and represent time-averages for the period 1987-1996 on the 3-digit SIC level.
L&B	Land & [improvements (*ppenli*) + buildings (*ppenb*) + construction in progress (*ppenc*)] / total assets (*at*). Values are net of depreciation and represent time-averages for the period 1987-1996 on the 3-digit SIC level.
Book leverage	[Long-term debt (*dltt*) + debt in current liabilities (*dlc*)] / Total assets (*at*)
Tobin's Q	[Common shares outstanding(*csho*) × Price close - Annual - Calendar ($prcc_c$) + debt in current liabilities (*dlc*) + long-term debt (*dltt*)] / Total assets (*at*)
Firm size	Total assets (*at*)
Sales	Sales/turnover (net) (*sale*)
ROA	Operating income before depreciation (*oibdp*) / Total assets (*at*)
Debt/EBITDA	[Long-term debt (*dltt*) + debt in current liabilities (*dlc*)] / [Operating income before depreciation (*oibdp*) + Depreciation and amortization (*dp*). We create dummy variables for the upper quartile and negative values.
Rating	Equal to 1 if a firm has any rating from Standard & Poors, Fitch, Moody's, or Duffs & Phelps.
Equity issuance	Common Shares Issued (*cshi*) × Price close - Annual - Calendar ($prcc_c$) / Total assets (*at*).
Equity equity	[Common Shares Issued (*cshi*) × Price close - Annual - Calendar ($prcc_c$) + Sale of Common and Preferred Stock (*sstk*) - Purchase of Common and Preferred Stock (*prstkc*)] / Total assets (*at*).
Retained earnings	retained earnings (*re*) / total assets (*at*).
Dividend payout	total dividends (*dvt*) / operating income before depreciation (*oibdp*).

Variable	Definition
Contract-Level Variables (Dealscan)	
Syndicated	Equal to 1 if a firm has received a syndicated loan.
Lender relation	Equal to 1 if a firm has received a loan from the lead arranger bank before. Proxy for an existing lender-borrower relationship.
Loan purpose	vector of dummy variables for the different loan purposes.
$M\&E_{sec}$	Equal to 1 if collateral used in the contract coded as ”Property & Equipment” or ”Plant”; or if the comment section includes ”achine” or ”equipmen” while excluding ”Land”, ”land”, ”uilding”, ”ortgage”, ”operty”, ”operties”, ”estate”, and ”facilit” and is not coded in the contract as ”Real Estate”. Equal to 0 otherwise and where $Land\&Building_{sec}$ is 1.
$L\&B_{sec}$	Equal to 1 if collateral used in the contract is coded as ”Real Estate” or ”Cash and Marketable Securities”; or if the comment section includes ”Land”, ”land”, ”uilding”, ”ortgage”, ”operty”, ”operties”, ”estate”, or ”facilit” while excluding ”achine” or ”equipmen” and is not coded in the contract as ”Property & Equipment” or ”Plant”. Equal to 0 otherwise and where $Machinery\&Equipment_{sec}$ is 1.
Industry-Level Variables	
R&D	Average industry level R&D expenditure for 1987-2014. Obtained from the National Science Foundation’s Survey of Industry Research and Development (SIRD).
Productivity	Average industry level annual percentage change in labor productivity for 1987-2014. Obtained from the Labor Productivity and Costs (LPC) tables of the Bureau of Labor Statistics (BLS).

Online Appendix

This online appendix accompanies the paper "Liquidation Values, Claim Priority, and Productivity" by Jan Keil and Karsten Mller. Sections A to E below provide some additional empirical results on the role of liquidation values. In section A, we employ the staggered corporate tax hikes assembled by Heider and Ljungqvist (2015) as exogenous shock to credit demand to underscore that our results are not driven by omitted firm variables. In the remaining sections B to E, we plot additional tables using alternative measures of our main proxies for liquidation values, and replicate our findings using classic capital structure regressions.

A1. Additional Evidence: Staggered Corporate Tax Increases as Exogenous Shock to Credit Demand

As we establish above, liquidation values are consistently related to loan terms. We also argue that the stringent econometric set-up makes it unlikely that unobserved demand effects or endogeneity bias our results. In this section, we attempt to overcome any remaining concerns by employing a natural experiment based on state-level increases in corporate income tax rates obtained from Heider and Ljungqvist (2015). They show that these staggered events are plausibly unrelated to economic fundamentals, and are followed by strong increases in leverage in the year after their introduction. They estimate a large effect of a 40 basis points increase in leverage following a one percentage point increase in taxes.

We retrieve data on 43 state-level corporate tax increases in 24 states between 1989 and 2012 from their article. These tax hikes overlap with 3,590 loan facilities in our matched dataset and are coded as dummy variables equal to 1 when taxes were raised.[48] For firms to be affected by these increases, they have to make

[48] We do not look at tax cuts, which they find to have no effect on leverage.

up a non-negligible amount in the overall tax burden. In our matched sample, the average (median) sample firm pays 28.6% (12.5%) of their overall income taxes on the state level.[49] Note that what matters most for our purposes is not the magnitude of the state-wise tax burden but the variation that is created by their staggered introduction.

Our strategy is to expose our loan contract terms to the common state-level credit demand shock created by the tax increases. All firms in a state where a tax hike is implemented have an incentive to raise new debt. Since we thoroughly account for possible determinants of firms to do so, such as firm size and existing leverage levels, there is no reason to suspect that our liquidation value proxies capture omitted effects.

Interacting our measures of asset redeployability with the tax changes makes it implausible that our estimates are driven by firm-specific demand factors. For demand factors to drive our results, one would have to argue that firms are subject to demand shocks that perfectly coincide with politically motivated tax increases. Further, they would have to be ordered in magnitude according to their industry's relative liquidation values. For example, all firms in New Jersey in 2006 would have to be subject to a firm-level shock to investment opportunities that is strongest for firms with the most redeployable assets, which seems unlikely. Instead, the effect we are observing as a reaction to the exogenous tax shocks will be determined by the lenders' willingness to grant credit.

We specify our estimation in a difference-in-difference set-up as follows:

$$
\begin{aligned}
LoanTerm_{ijst} = {} & \beta_1 TaxHike_{s,t-1} + \beta_2 TaxHike_{s,t-1} \times Redeployability_i \\
& + \gamma FirmControls_{it} + \delta ContractControls_{jt} \\
& + \alpha \mathbf{\Lambda_{kbst}} + \varepsilon_{ijst},
\end{aligned} \tag{3}
$$

where $LoanTerm$ is one of the loan contract terms (amount, interest rate, matu-

[49] This compares with an average (median) of 21% (13.7%) reported by Heider and Ljungqvist (2015).

rity, secured, covenants, borrower base). $TaxHike$ is a dummy variable indicating whether corporate taxes were raised in state s in year t.[50] The estimate of β_2 gives us the impact of liquidation values on loan terms that is plausibly independent of demand factors. We follow Heider and Ljungqvist (2015) and use the lagged tax changes to allow firms time to react.[51] We continue to saturate the model with our fixed effects vector $\boldsymbol{\Lambda}$, and only report the results including $state \times year$ dummies to accommodate other state-level determinants.

Table A1 shows the results of this exercise, where any economic or political changes on the state-level are accommodated by the $state \times year$ dummies. We see the by now familiar signs for machinery and equipment, which attract a smaller loan volume and higher interest rates. The coefficients for $loan\,volume$ and the $interest\,rate$ are precisely estimated despite the inclusion of all of our stringent interacted fixed effects, suggesting that our earlier estimations are not driven by unobserved time-varying firm effects. Both $maturity$ and $secured$ attract the expected negative and positive sign, respectively, but the estimates lack statistical significance. They are, however, complemented by the opposite signs for *Land & Buildings* in the second row, which is estimated precisely for the maturity.

It is worth to mention the estimates of our land and building proxy on $volume$ and $interest$ in columns 2 and 3, which have the opposite of the expected sign but are very imprecisely estimated. Taking a look at the standard errors is instructive: the implied t-statistic are small. Given that we only use the 43 tax hikes from Heider and Ljungqvist (2015), the effects are likely to be zero and driven by the sample selection. The same is true for the estimates for the number of financial covenants and borrower base contracts. These results further lends some weight to the argument that the effects of asset redeployability are slightly

[50] Note that the simple tax hike dummy is nested once state-year fixed effects α_{st} are included.

[51] In line with the evidence in Heider and Ljungqvist (2015), the coefficients of our interaction terms are not significant if we use contemporaneous values for $TaxHike$ or any other lags and leads in almost all cases. This is further support for our exogeneity argument. The results are available upon request.

asymmetric, with the disadvantages of machinery and equipment for loan volume and interest rate spread outweighing the benefits of land and buildings.

Comparing the industries at the 10% and 90% percentiles with our experimental approach gives a much more accurate picture of the economic importance of liquidation values. Indeed, the estimated effects are much larger, which is hardly surprising given that our main estimation above attempts to explain the terms of almost 20,000 loan contract terms over a 27-year period. When raising debt in likely response to the demand shock created by the tax increases, a 10-90 shift in *Machinery & Equipment* implies 21.6% lower loan volume (48,000,000 USD), 35.2% higher interest rates (81 basis points), and 11.1% shorter maturities (5 months). While not estimated precisely, the coefficients for *secured* and *bbase* imply a 6.7% and 9.9% higher likelihood in the contract, respectively. The only reasonably precisely estimated corresponding values for *Land & Buildings* imply 27% or about 12 months longer maturities (t=2.01) and 8.5% less collateralization (t=1.28).

Overall, the experimental approach confirms our main results: firms in industries with lower liquidation values receive smaller loans at higher interest rates and shorter maturities, and are more likely to be secured. The estimated magnitudes are large, with the range of liquidation values implying differences up to 56.1% in loan volume (*M&E*), around 400 basis points in interest rates (*M&E*), about 14 months in maturity (*L&B*), and 30.4% lower likelihood of collateralization (*L&B*).[52]

[52] These calculations are based on the range of values in *Machinery & Equipment* and *Land & Buildings*, which equal 0.85 and 0.65, respectively. More precisely: $EXP(-0.974 * 0.85) - 1 = -0.561$; $EXP(1.207 * 0.85) - 1 = 1.772$, where $(230.40 * 1.772) = 408\,basis\,points$; $EXP(1.327 * 0.65) - 1 = 0.328$, where $0.328 * 43.08 = 14.13\,months$; and $-0.47 * 0.65 = -0.304$.

Table A1: Corporate Tax Increases as Exogeneous Credit Demand Shocks

	loan volume		*interest rate*		*maturity*		*secured*		*covenants*		*bbase*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
$M\&E \times tax\,(t-1)$	-0.974		1.207***		-0.470		0.269		-0.410		0.391	
	(0.599)		(0.441)		(0.539)		(0.272)		(0.508)		(0.260)	
$L\&B \times tax\,(t-1)$		-0.119		0.383		1.327**		-0.470		-0.289		0.392
		(0.749)		(0.560)		(0.660)		(0.368)		(0.486)		(0.306)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Industry*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13,861	13,861	13,861	13,861	13,861	13,861	13,861	13,861	9,603	9,603	13,861	13,861
R^2	0.871	0.871	0.812	0.812	0.550	0.550	0.674	0.674	0.611	0.611	0.485	0.485

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. $M\&E \times tax\,(t-1)$ and $L\&B \times tax\,(t-1)$ are interaction effects of *M&E* and *L&B* with a dummy variable that indicates if a corporate tax hike in the company headquarter's state occurred in the previous year $(t-1)$. The contract terms *loan volume*, *interest rate*, *maturity*, and *secured* are included as controls. *secured* is a dummy variable for the loan being secured (1) or not (0). Contract and firm level control variables with higher orders are also included. "Higher order" includes squared and cubed values of all firm control variables.The same is the case for the regular and interactive fixed effects for the loan purpose, year, industry and state. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

A2. Baseline Estimations with Credit Ratings

Credit ratings are only available for a sub-set of our matched dataset. In order to preserve a reasonable sample size, we only control for credit risk by including a dummy for whether a firm has a credit rating and two dummies for the debt to cash flow ratio in the main estimations. In this section, we show that our findings are not driven by abstracting from firm risk.

Table A2: Liquidation Values and Loan Terms (Estimations Include Credit Ratings)

	loan volume				*interest rate*				*maturity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
M&E	-0.909***	-0.624***			0.162**	0.270**			-0.157	-0.273*		
	(0.211)	(0.214)			(0.081)	(0.106)			(0.110)	(0.141)		
L&B			0.442*	0.466			-0.140	-0.178			0.001	0.319
			(0.240)	(0.284)			(0.125)	(0.157)			(0.157)	(0.198)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	7,459	6,465	7,459	6,465	7,459	6,465	7,459	6,465	7,459	6,465	7,459	6,465
R^2	0.617	0.794	0.615	0.794	0.794	0.916	0.794	0.916	0.362	0.622	0.362	0.621

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. The contract terms *loan volume*, *interest rate*, and *maturity* are included as controls. Contract and firm level control variables with higher orders are also included. "Higher order" includes squared and cubed values of all firm control variables.The same is the case for the regular and interactive fixed effects for the loan purpose, year, industry and state. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table A3: Liquidation Values and Claim Priority (Estimations Include Credit Ratings)

	secured				*covenant*				*bbase*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
M&E	0.166**	0.184*			0.169	0.071			0.152**	0.202***		
	(0.073)	(0.100)			(0.103)	(0.138)			(0.063)	(0.077)		
L&B			-0.230**	-0.097			-0.192	-0.252			-0.043	-0.219*
			(0.092)	(0.134)			(0.175)	(0.211)			(0.081)	(0.119)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	7,459	6,465	7,459	6,465	5,429	4,718	5,429	4,718	7,459	6,465	7,459	6,465
R^2	0.611	0.823	0.611	0.822	0.411	0.767	0.411	0.767	0.225	0.562	0.224	0.561

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets. *secured* is a dummy variable for the loan being secured (1) or not (0). *covenant* is the number of financial covenants in the loan contract, *bbase* is a dummy indicating the if the loan contract contains a borrower base arrangement (1) or not (0). Contract and firm level control variables with higher orders are also included. "Higher order" includes squared and cubed values of all firm control variables.The same is the case for the regular and interactive fixed effects for the loan purpose, year, industry and state. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

A3. Alternative Measures of Liquidation Values

The use of our variables to approximate liquidation values is firmly grounded in the literature. However, for robustness we present the results for a range of related alternative proxies in this section.

First, we replace the time averages with time-varying data on real asset structure obtained from the BEA. Industry level data on fixed assets comes from the National Income and Product Account (NIPA) tables provided by the Bureau of Economic Analysis (BEA) at the Department of Commerce. Variables are computed from three Fixed Assets Accounts Tables, Table 3.1E, Table 3.1S, and Table 1BU. These have the advantage that they do not only capture changes of industry asset structures over time but are also more comprehensive than the Compustat data, which is only based on public firms. Since the values vary by year, the estimates may however be subject to more significant endogeneity concerns. Table A4 shows our baseline results with the BEA data on *Machinery & Equipment* and *Land & Buildings*.[53]

Second, we replace our main variables by proxies constructed from the gross data in Compustat on *Machinery & Equipment* ($fate$) and *Land & Buildings* ($fatb+fatp$). While this data is available for our entire sample period, the values are not adjusted for depreciation. We thus manually adjust the gross data using the depreciation values available for all fixed assets ($dpact$), which refers to total gross fixed assets ($ppegt$). In particular, we use the share of *Machinery & Equipment* and *Land & Buildings* in gross fixed assets.[54]. In line with our main proxies, we average the values by year on the 3-digit SIC level[55] Results can be reviewed in table A5.

Third, we show that our results are not driven by using sector averages by re-

[53]Note that the estimates are equivalent but of opposite sign because the variables add up to 1.

[54]The exact calculations are $Land\&Buildings = [fatb + fatp] - [(fatb + fatp)/ppegt] * dpact$ and $Machinery\&Equipment = fate - [fate/ppegt] * dpact$. As for the variables using net values, we scale both over total assets (at).

[55]The results are unchanged when we instead use median values.

defining our main proxy variables as medians on the SIC 3-digit level. Table A6 shows the results of this exercise. All main results for all three alternatives are robust and at times are even more precisely estimated.

Table A4: Alternative Explanatory Variables: BEA Data

	loan volume				*interest rate*				*maturity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
$M\&E_{BEA}$	-0.411***	-0.486***			0.042	0.073			0.022	-0.121		
	(0.120)	(0.119)			(0.061)	(0.072)			(0.064)	(0.077)		
$L\&B_{BEA}$			0.411***	0.486***			-0.042	-0.073			-0.022	0.121
			(0.120)	(0.119)			(0.061)	(0.072)			(0.064)	(0.077)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	16,956	14,786	16,956	14,786	16,956	14,786	16,956	14,786	16,956	14,786	16,956	14,786
R^2	0.797	0.872	0.797	0.872	0.617	0.798	0.617	0.798	0.312	0.557	0.312	0.557

The columns of this table lists regressions of loan terms on *Machinery & Equipment* and *Land & Buildings*. $M\&E_{BEA}$ and $L\&B_{BEA}$ are annual BEA industry data on machinery and equipment and land and buildings. The contract terms *loan volume*, *interest rate*, and *maturity* are included as controls. Contract and firm level control variables with higher orders are also included. The same is the case for the regular and interactive fixed effects for the loan purpose, year, industry and state. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table A5: Alternative Explanatory Variables: Gross Assets

	loan volume				*interest rate*				*maturity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
$M\&E_{gross}$	-0.723***	-0.658***			0.231***	0.190**			0.057	-0.107		
	(0.170)	(0.164)			(0.080)	(0.093)			(0.086)	(0.102)		
$L\&B_{gross}$			0.200	0.217			-0.045	0.051			0.355**	0.572***
			(0.277)	(0.247)			(0.149)	(0.167)			(0.157)	(0.181)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	19,094	16,778	19,094	16,778	19,094	16,778	19,094	16,778	19,094	16,778	19,094	16,778
R^2	0.797	0.867	0.796	0.867	0.623	0.792	0.622	0.791	0.311	0.544	0.311	0.544

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry means of *Machinery & Equipment* and of *Land & Buildings* in total assets computed in gross terms. The contract terms *loan volume*, *interest rate*, and *maturity* are included as controls. Contract and firm level control variables with higher orders are also included. Higher order includes squared and cubed values of all firm control variables. The same is the case for the regular and interactive fixed effects for the loan purpose, year, industry and state. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

Table A6: Alternative Explanatory Variables: Sector Medians

	loan volume				*interest rate*				*maturity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidation Value Proxies												
$M\&E_{median}$	-0.585***	-0.424***			0.237***	0.253***			-0.054	-0.145		
	(0.155)	(0.151)			(0.074)	(0.087)			(0.081)	(0.093)		
$L\&B_{median}$			-0.074	0.043			-0.157	-0.089			0.281**	0.318**
			(0.178)	(0.154)			(0.097)	(0.115)			(0.117)	(0.127)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	18,965	16,660	18,965	16,660	18,965	16,660	18,965	16,660	18,965	16,660	18,965	16,660
R^2	0.796	0.867	0.795	0.866	0.622	0.791	0.622	0.791	0.311	0.545	0.311	0.545

The columns of this table lists regressions of loan terms on *Machinery & Equipment* (*M&E*) and *Land & Buildings* (*L&B*). The latter are the 3-digit SIC industry medians of *Machinery & Equipment* and of *Land & Buildings* in total assets. The contract terms *loan volume*, *interest rate*, and *maturity* are included as controls. Contract and firm level control variables with higher orders are also included. "Higher order" includes squared and cubed values of all firm control variables.The same is the case for the regular and interactive fixed effects for the loan purpose, year, industry and state. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

A4. Replication with Standard Capital Structure Regressions

To show that our results are not driven by the smaller matched sample, we replicate our main results in standard capital structure regressions of the following type:

$$Leverage_{it} = \alpha_i + \alpha_t + \beta Redeployability_{jt} + \gamma FirmControls_{it} + \varepsilon_{it}, \tag{5}$$

where $Redeployability$ is defined on the industry level using the BEA variables (as percentage of tangible assets)[56]; α_i and α_t are firm and time dummies; and $FirmControls$ are the same control variables we have used throughout the paper, excluding book leverage. Note that we cannot use our main proxy variables in this type of regression since they are time-invariant and thus perfectly collinear with the firm fixed-effects α_i.

We use three different measures of leverage. First, we take the standard *Book Leverage* which was also used as a control variable throughout the paper (total debt over total assets). Second, we treat cash (Compustat *che*) as negative debt and subtract it from total debt before scaling over assets ($Net\ Leverage$). Third, we use $Market\ Leverage$, defined as total debt over total debt plus total equity (Compustat $[dlc + dltt]/[csho * prcc_c + dlc + dltt]$. We further look at the share of long-term debt in total liabilities (Compustat dlt/lt).

Table A7 shows the results of this exercise. All variables support our main point that higher liquidation values go hand in hand with higher leverage, and further more long-term debt.

[56]The results are similar when we scale *Equipment* and *Structures* by total assets. However, as explained in section V above, this introduces a bias by incorporating intangibles.

Table A7: Standard Capital Structure Regression Results

	Book Leverage (1)	Net Leverage (2)	Market Leverage (3)	Long-Term Debt Share (4)
M&E	-0.174***	-0.254***	-0.151***	-0.071*
	(0.067)	(0.078)	(0.040)	(0.042)
Controls				
Firm	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes
Fixed Effects				
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Obs.	107,518	107,505	107,517	107,511
R^2	0.596	0.676	0.763	0.689

This table lists coefficients from regressions on different leverage variables. Standard errors clustered by firms are in brackets under the respective coefficient. Each column represents a regression. All other firm level control variables with higher orders are included in the regressions but omitted for clarity. The same is the case for the intercept as well as firm and year dummies. *M&E* is the share of *Machines&Equipment* in total tangible assets obtained from the BEA. Debt includes debt in current liabilities and long-term debt. Net debt excludes cash and short-term investments. * indicates statistical significance at 1%, ** at 5% and *** at 10%.

A5. *Alternative Coding of Contract-Level Collateral*

The Dealscan package specifying the type of security used in the contract is unfortunately very noisy. As a robustness check, we also report the results for the classification into specific and non-specific assets as in Liberti and Mian (2010). The results are very similar. We redefine the coding as follows:

$Specific_{sec}$. Equal to 1 if collateral used in the contract coded as ”Accounts Receivable and Inventory”, ”Property & Equipment”, ”Intangibles”, ”Plant”, ”Agency Guarantee”, ”Ownership of Options/Warrants”, ”Patents”, ”Other”; or if the comment section includes ”achine”, ”quipmen”, ”etter”, ”uarante”, ”ontract order”, ”atent”, ”ntangible”, ”port letter”, ”nventor”, ”eceivable”, ”romissory” while excluding ”Land”, ”land”, ”uilding”, ”ortgage”, ”operty”, ”operties”, ”estate”, ”facilit”, ”cash”, ”Cash”, ”oney”, ”securit”, ”hares”, ”bond, ”Bond”, or ”stock” and is not coded in the contract as ”Real Estate” or ”Cash and Marketable Securities”. Equal to 0 otherwise and where $Non-specific_{sec}$ is 1.

$Non-specific_{sec}$. Equal to 1 if collateral used in the contract is coded as ”Real Estate” or ”Cash and Marketable Securities”; or if the comment section includes ”Land”, ”land”, ”uilding”, ”ortgage”, ”operty”, ”operties”, ”estate”, ”facilit”, ”cash”, ”Cash”, ”oney”, ”securit”, ”hares”, ”bond, ”Bond”, or ”stock” while excluding ”achine”, ”quipmen”, ”etter”, ”uarante”, ”ontract order”, ”atent”, ”ntangible”, ”port letter”, ”nventor”, ”eceivable”, ”romissory” and is not coded in the contract as ”Accounts Receivable and Inventory”, ”Property & Equipment”, ”Intangibles”, ”Plant”, ”Agency Guarantee”, ”Ownership of Options/Warrants”, ”Patents”, ”Other”. Equal to 0 otherwise and where $Specific_{sec}$ is 1.

Table A8: Contract-Level Security Regression Results with Liberti-Mian Classification: Loan Terms

	loan volume				*interest rate*				*maturity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Main explanatory variables												
$M\&E_{LM}$	-0.054	-0.048			0.005	-0.005			-0.021	-0.020		
	(0.034)	(0.036)			(0.018)	(0.019)			(0.021)	(0.026)		
$L\&B_{LM}$			0.127***	0.173***			-0.021	-0.003			0.031	0.046
			(0.034)	(0.045)			(0.024)	(0.026)			(0.021)	(0.030)
Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Higher Order	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
Year	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-
Industry*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Bank*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
State*Year	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
Obs.	8,001	7,041	8,001	7,041	8,001	7,041	8,001	7,041	8,001	7,041	8,001	7,041
R^2	0.742	0.838	0.743	0.838	0.368	0.708	0.369	0.708	0.375	0.633	0.375	0.633

The columns of this table lists regressions of loan terms on *Machinery & Equipment* and *Land & Buildings*. $M\&E_{LM}$ is equal to 1 if the security in the loan is classified as machinery and equipment or plant; $L\&B_{LM}$ is equal to 1 for land and buildings or cash and marketable securities. They are 0 otherwise. The contract terms *loan volume*, *interest rate*, and *maturity* are included as controls. Contract and firm level control variables with higher orders are also included. "Higher order" includes squared and cubed values of all firm control variables.The same is the case for the regular and interactive fixed effects for the loan purpose, year, industry and state. Standard errors are in brackets under the respective coefficient. * indicates statistical significance at 1%, ** at 5% and *** at 10%.