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Who needs big banks? The real effects of bank size on outcomes of large US borrowers

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ABSTRACT

We examine how bank size affects borrowers, when information asymmetry is not particularly severe. Our sample comprises 20,806 loan facilities granted to 3625 US public firms. After minimizing endogeneity concerns, we find that there is a positive relation between bank size and firm value, after the origination of the loan. Firms that borrow from large banks invest more, grow faster and have higher risk, proxied by earnings volatility. The effects are concentrated in borrowers which are ex-ante (pre-loan) safer (low leverage or high *Z*-score) and muted, but not negative, in riskier firms. We highlight the bright side of large banks.

1. Introduction and related literature

We know that large banks played a leading role in the recent global financial crisis, and their distress has had severe negative consequences for the real economy. This has triggered an on-going debate on the optimal size of banks resulting in a series of policy measures aimed at reducing the risk of large or systemically important financial institutions. For example, the Basel Committee suggests a capital surcharge of up to 2.5% on banks deemed to be systemically important. These policies encourage banks to reduce their size or split their activities. While the effects of bank size on systemic risk have been widely studied in the existing literature (see e.g. Laeven et al., 2016; Bertay et al., 2013; Brownlees and Engle, 2017), the effects of bank size on the real outcomes of firms remain relatively unexplored. Hence, the policies motivated by too-big-to-fail concerns may have unintended consequences for corporate borrowers. In this paper, we empirically examine the effects of the size of the lending banks on the outcomes of large, publicly traded borrowers.

Theory predicts that small banks have a comparative advantage in producing soft information (Stein, 2002). Small, privately held firms face severe information asymmetry and rely on potential lenders producing soft information for making lending decisions. This suggests that small banks have a comparative advantage in monitoring small, privately held firms and there is substantial evidence in support of this hypothesis (e.g., Berger et al., 2005). However, the soft information advantage is reduced

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significantly when lending to large, publicly traded firms. This observation motivates our research question. Specifically, we examine the effect of bank size on the operating performance and investment policies of large, publicly traded borrowers in the US. In this regard, we also contribute to an emerging literature that studies the real effects of bank lending on firm outcomes.

Large banks benefit from their own set of advantages. The too-big-to-fail guarantees (which may be implicit or explicit) reduce the large banks' cost of capital. Further, large banks benefit from scale economies via increased cost efficiency (see e.g., Hughes and Mester, 2013 and Wheelock and Wilson, 2012, 2015). We conjecture that this advantage spills over into the real sector, to the firms that borrow from large banks. Therefore, we hypothesise that bank size has a positive effect on (large) borrower value and operating performance. We consider the following channel. If large banks pass on some of their cost savings to their borrowers, it would reduce the borrower's cost of capital and increase its investment opportunities. Previously negative NPV projects become positive NPV, due to the lower cost of capital. Therefore, firms borrowing from large banks gain value as they invest more (in positive NPV projects).

Our sample consists of 20,806 loan facilities granted to 3625 publicly traded US companies between 1992 and 2015. We first assess the effect of bank size on firm's performance. Bank size is the total asset of the bank making the loan. Our main proxy for the firm's performance is the Return on Assets, *ROA*, which is an accounting-based measure. For robustness, we also use the industry-adjusted variant of *ROA* and a market based proxy, the *Tobin's Q*. We find that there is a positive relationship between bank size and firm performance, after the origination of the loan. A 10% increase in bank size leads to an increase in *ROA* by 0.8%; the magnitude of the effect is important considering that it represents 24% of the average post-loan *ROA* (average post-loan *ROA* is 3.3%).

In terms of firm-level investment, we find that post-loan, firm investment increases with bank size. Both components of investment, capital expenditure and *R&D* spending, increase with bank size. Additionally, post-loan volatility in earnings increases with bank size. Consistent with higher investment, we find that firms borrowing from large banks grow faster (in terms of total assets and sales) over the tenor of the loan. Overall, this suggests that firms in our sample that borrow from large banks invest more and increase their risk, which (at least partially) explains our main results that firm performance increases with bank size. The positive link between investment and performance is consistent with Jiang et al. (2015) who find that higher product market competition increases investment, which leads to stronger performance.

One would expect that an increase in risk will be value-enhancing only for a subset of firms that are operating at a lower than optimal level of risk. To test this hypothesis, we split up our sample into ex-ante safe and risky firms (low leverage or high *Z*-score firms are safer). Consistent with our predictions, we find evidence that the observed effects are mostly concentrated in ex-ante safer firms. The effects are generally neutral in the riskier subset of firms.

According to Berger et al. (2005), banks and firms match on size, i.e., big banks lend to bigger firms and small banks lend to smaller firms. Another concern is that there may be a reverse causality if firms choose which bank to borrow from based on their investment needs. With this in mind, we take two steps: first, we restrict our sample to only large, publicly traded US firms. Second, similar to Berger et al. (2005), we use an instrumental variable approach to account for the endogenous choice of bank size by the borrower.

We instrument bank size with the Branching Restrictiveness Index (BRI) of Rice and Strahan (2010). This variable captures the state's lending environment, which we argue (partially) determines a borrower's choice of bank size. To be valid, an instrument should be exogenous to the dependent variable. Kroszner and Strahan (1999) (and others, see Section 4.1 for a more detailed background) document that bank competition in the state is shaped by the power struggles between special interest groups and the general political landscape. Therefore, the lending environment is plausibly exogenous to our dependent variable, the borrower's outcomes.

There is a large literature that studies the effect of bank financing on borrowers. Diamond (1984) theoretically studies the comparative advantage of banks in resolving post-lending moral hazard problems. James (1987), Lummer and McConnell (1989) and more recently, Gande and Saunders (2012) find empirical support that bank financing adds value to firms. These studies treat the effect of bank financing on the borrowing firm as homogeneous across different bank types. In contrast, in our case, the effect of bank financing varies across bank size which is a proxy for scale effects.

There are several studies showing that bank size is an important determinant of the nature of the bank-borrower relationship. In the context of bank lending to small firms, Berger et al. (2005) find evidence that small banks are better able to generate and process soft information and have stronger relationships with borrowers. As a result, small banks are relatively better equipped to relax the credit constraints of small firms (see also, Cole et al., 2004 and DeYoung et al., 2004). We complement this strand of the literature as we study the effect of bank size on large, publicly traded firms. This is an important exercise as the dynamics of bank monitoring are different in the context of lending to large, publicly traded firms. We argue that soft information is less relevant for these firms, insomuch as they are informationally more transparent.

Our study also relates to an emerging strand of the literature that examines the effect of the bank-borrower relationship on borrower value (performance). Dass and Massa (2011) examine the effect of the relationship on corporate governance (positive) and market liquidity (negative). On balance, they find that firm value is positively affected by the bank-borrower relationship. Qian and Yeung (2015) find that the effect of bank financing on governance depends on the efficiency in the banking sector. Delis et al. (2017) find that bank market power positively affects the performance of firms.

Some studies also look specifically at the effect of bank lending on corporate investment. Chava and Purnanandam (2011) find that negative shocks to banks have real negative consequences for borrowers (see also Carvalho et al., 2015). During a banking crisis, bank-dependent borrowers suffer larger valuation losses and subsequently experience a higher decline in their capital expenditure and profitability. Aslan (2016) finds that lending relationships significantly affect leverage ratios, issuance choices and investment structures in relationship borrowers. Gonzalez (2016) finds that stronger bank competition is associated with greater reduction in corporate investment during the crisis.

Our contribution to this strand of the literature is as follows: we show that over and above the observable aspects of the lending relationships (such as the existing relationship, cost of debt), unobservable factors captured by bank size (e.g., scale effects), also affect the borrower's outcomes such as performance and investment. Further, we link our findings to the observed riskiness of the borrower.

2. Hypothesis statement

The literature on soft information (e.g., Berger et al., 2005 and DeYoung et al., 2004) find that small banks are better at collecting and processing soft information due to their simpler structures. This comparative advantage allows small banks to lend more effectively to small, opaque firms. However, soft information is arguably less important for large, publicly traded firms. Publicly traded firms experience a greater level of scrutiny and are required by regulation to meet certain disclosure standards which results in a greater level of transparency. Hence, the asymmetric information issue is less severe for these firms.

Additionally, large banks benefit from scale effects in cost saving (see e.g., Hughes and Mester, 2013 and Wheelock and Wilson, 2012, 2015) and the too-big-to-fail guarantees. If large banks pass on some of these savings to their borrowers, it reduces the firm's cost of capital. This results in increased value for firms as some previously negative NPV projects become positive NPV and the level of investment increases.

We state our hypothesis for large, publicly traded firms:

H1: *Bank size has a positive effect on borrower value and performance, after the origination of the loan.*
H2: *Bank size has a positive effect on the level of investment and risk, after the origination of the loan.*

Finally, as we hypothesise that an increase in value comes from an increase in the level of investment (and hence, total business risk), we expect that the observed effects would be concentrated in ex-ante safer firms. Our argument is that an increase in risk in ex-ante riskier firms would possibly be value-destroying, rather than value-enhancing.

H3: *The positive effects of bank size on firm value and investment are concentrated in ex-ante safer firms.*

The effects of *Banksize* on ex-ante riskier firms are unclear. If big banks indiscriminately (of risk) allow higher risk taking, this would potentially destroy value in riskier borrowers. However, if banks exercise discretion, i.e., pass on lower costs to safer firms only, then we expect the effects of *Banksize* on riskier firms to be neutral.

3. Data

The data are compiled from several sources: the loan level data comes from the DealScan database provided by the Loan Pricing Corporation (LPC). Bank size information is obtained from the financial statements in the BankScope database provided by Bureau van Dijk. Finally, firm level variables are obtained from the merged CRSP/Compustat database and the I/B/E/S database.

3.1. Sample construction

DealScan provides information on the loans issued to large public companies, both at the facility level and deal level. In our study, we collect the data at the facility level and all facilities issued to publicly listed US companies during the period 1992-2015 are initially selected. We exclude the facilities issued to the financial services companies (SIC codes from 6000 to 6999). We drop all facilities that are issued by non-bank financial institutions. Consequently, we end up with a total of 20,806 facilities and 3625 borrowers. In this sample, 2374 companies have two or more facilities in one year. For our regression analysis, we aggregate the facility-level data to the firm-year level. If there are multiple facilities issued to a borrower in a particular year, we combine them into one observation. The final sample consists of 12,217 observations.[1]

3.2. Linking DealScan and BankScope

Most facilities in DealScan are syndications issued by one or more lead arrangers and several participants. We focus on lead banks because the participants have limited contributions in originating and monitoring the loans. Following convention (see Campello and Gao, 2017), we classify lending banks by their ultimate parents. DealScan's Company dataset provides the lenders company's identifier, its parent's identifier and its ultimate-parent's identifier. Therefore, we easily observe the ultimate parent of each lender.

[1] The number of observations differs across regressions as necessary controls are not always available.

While DealScan provides the locations and names of banks, the accounting data of banks are not contained in it. Thus we obtain the accounting information of banks from BankScope. Since there is no common identifier between DealScan and BankScope, we manually match these two datasets by using the bank names and locations. The matching is initially done by the fuzzy merge algorithm in STATA using bank names and locations. Since the fuzzy merge is based on a bigram string comparator, it is imperfect; so, we manually review all matching results.

We further increase our matching accuracy by checking the M&A activities of a facility-issuing bank in the year in which the facility is granted. To implement this, we use the official M&A records from the Chicago Fed's website. BankScope provides the 'Bank History' and 'Previous Name' variables, which show the M&A activities and name changes of a bank. We cross check these datasets in order to achieve an accurate dynamic match across different years. Finally, if the lender's name is not recognizable, we identify it by tracking its subsidiaries in DealScan, searching this name among the bank's previous names listed in BankScope or searching online to find news articles containing similar bank names. In this way, we link the lender ultimate-parent identifier in DealScan to the bank identifier in BankScope, 'bvdidnum'. Since we are interested in the ultimate parent bank's asset, we use the consolidated financial statements in our analysis.

We use Imperial Bank (companyid = 5985) in DealScan as an example to illustrate the matching process. First, we use the fuzzy merge in STATA using the bank name and bank location (California, US), which generates the matching result, Imperial Bank (BankScope bvdidnum = US131942440). However, after reviewing the match, we identify that the match given by the algorithm is a commercial bank, not the bank holding company that we are interested in, although it has the same name and location. Then we manually search similar names in BankScope and find that the correct match is Imperial Bancorp (BankScope bvdidnum = US952575576) at the BHC level. Next, we check the M&A history of this bank. We find that Comerica Incorporated acquired Imperial Bancorp in January, 2001. Therefore, after 2001, the ultimate-parent companyid, 5985, should be linked with Comerica Incorporated (BankScope bvdidnum = US381998421) instead of Imperial Bancorp (BankScope bvdidnum = US952575576). Then we check the BankScope indices under these bvdidnums (i.e. US952575576 and US381998421) and use the indices using consolidated financial statements. Finally, Imperial Bank is linked with Imperial Bancorp (BankScope Index = 34570) prior to the acquisition in 2001 and Comerica Incorporated (BankScope Index = 34043), thereafter.

3.3. Firm characteristics

Firm-level accounting data are obtained from the Merged CRSP/Compustat database. Since DealScan does not provide a common identifier as CRSP/Compustat, we use the DealScan-Compustat link file provided by Michael Roberts (Chava and Roberts, 2008).

Dependent variables: Our main dependent variable is firm performance. The main proxy for performance is the return on assets, *ROA*, which is the income before extraordinary items divided by lagged assets. For robustness, we further use the industry-adjusted variant of *ROA* and *Tobin's Q*. *Tobin's Q* is calculated as the market value of equity plus the market value of debt over total assets. The *Tobin's Q* measure is forward looking and incorporates market expectations.
CAPEX is the ratio of the capital expenditure over the lagged asset. *R&D* is defined as the research and development expense over the lagged asset. *Investment* is defined as the sum of capital expenditure and *R&D* spending. Following convention, we replace the missing values of *R&D* with 0[2] (e.g., Billett et al., 2006). We use the volatility of earnings, $\sigma(EBIT)$, as a proxy for corporate risk. Finally, we consider the growth rates in Assets (log of total assets), Employees (number of employees) and Sales.

Control variables: *Firmsize* is the logarithm of the firm's total assets. *Leverage* is calculated as the long-term debt divided by total assets. To control for a firm's internal financing ability, we control for *Cash* and *Cashflow*, both scaled by the lagged asset. Asset *Tangibility* of a firm will also have an impact on the firm's financing ability and is measured as the ratio of property, plant and equipment over lagged assets. The firm's investment opportunity is represented by *Market-to-Book*, defined as the ratio of market equity over book equity. *Analyst* is obtained from the I/B/E/S Summary database and is defined as the number of analysts following the stock. *Credit* is a dummy variable that equals 1 if the borrowing firm has a credit rating, which implies access to alternate debt financing and 0, when it does not have a credit rating.
Following Bharath et al. (2007), $Rel_{m,k}$ is a dummy variable and captures the existence of a relationship between a bank, k and a firm, m, in the 5 years previous to the current facility. It equals 1 if there is a pre-existing relationship and 0, otherwise. Finally, we include all terms of loans (spread, number of covenants, whether the loan is secured or not and maturity) as controls.

Instruments: We instrument our main independent variable, *Banksize*, with the state-level Branching Restrictiveness Index (*BRI*) of Rice and Strahan (2010). *BRI* is an index of interstate branching restrictions that ranges from zero (least restrictive) to four (most restrictive). We take the time-weighted average BRI over the sample period as this reflects the intensity at which state regulators removed restrictions, reflecting the state's environment (see Table 1). We discuss the inclusion and exclusion restrictions in Section 4.1.

[2] Results are unchanged if we drop the missing values of *R&D*, but we lose around half of the observations.

Table 1
State-wise BRI scores.

Borrower's state	BRI score	Borrower's state	BRI score
Alabama	2.458	Nebraska	3
Alaska	1.667	Nevada	2.375
Arizona	2.042	New Hampshire	1.417
Arkansas	3	New Jersey	1.25
British Columbia	3	New Mexico	2.417
California	2.375	New York	1.917
Colorado	3	North Carolina	0.5
Connecticut	1.125	North Dakota	1.875
Delaware	2.375	Ohio	0.833
Florida	2.458	Oklahoma	1.75
Georgia	2.458	Ontario	3
Hawaii	1.333	Oregon	2.458
Idaho	2.375	Pennsylvania	0.5
Illinois	1.708	Puerto Rico	3
Indiana	1.333	Rhode Island	0.5
Iowa	3	South Carolina	2.417
Kansas	3	South Dakota	2.417
Kentucky	2.583	Tennessee	1.583
Louisiana	2.458	Texas	2.083
Maine	0.833	Utah	1.375
Maryland	0.5	Vermont	1
Massachusetts	1.25	Virginia	0.5
Michigan	0.5	Washington	2
Minnesota	2.458	West Virginia	1.375
Mississippi	3	Wisconsin	2.417
Missouri	3	Wyoming	2.458
Montana	3		

The Riegle-Neal Act removed the inter-state bank-branching restrictions in 1994. We assume the pre-1994 BRI to be 4 for all states. After the Riegle-Neal legislation, states began deregulations, which are listed in Johnson and Rice (2008) and Rice and Strahan (2010) . Finally, the Dodd-Frank Act of 2010 (section 613) removed any remaining restrictions and we set BRI to 0 for all states.

3.4. Bank characteristics

Our main independent variable is *Banksize*. We denote $Banksize_m$ for a borrower m as the total assets of its lender. Following convention (see Campello and Gao, 2017), we classify lending banks by their ultimate parents. As with the other independent variables, it is averaged over $[t-n, t-1]$. t is the start of a loan facility and the n refers to the tenor (or duration) of the facility. Further, if a facility contains multiple lead banks, we compute the average size of the lead banks. We focus on the lead banks to avoid including banks that have limited contribution in a specific facility. Wherever the contribution of each lead bank to the facility is available, we take the weighted average instead of the simple average. Suppose that there are K lead banks indexed by k, in the borrower m's facility,

$$Banksize_m = \sum_{k=1}^{K} \frac{(\text{loan amount})_k}{\text{total loan}} * (\text{total asset})_k. \tag{1}$$

If the loan amount that each bank contributes towards the loan facility is not available, the weight is simply $\frac{1}{K}$. Bank assets are measured in millions and we take the natural log of this variable in all regressions.

We also control for a number of bank level variables in our regressions. We use the *Income Diversity* (fraction of income in interest relative to non-interest) and *Activity Diversity* (fraction of earning assets in loans relative to non-loans) of Laeven and Levine, 2007 (see also Goetz et al., 2013). We also include *Bank Capital* and the log of the *Bank Operating Income*.

Finally, we control for the Herfindahl-Hirschman index (*HHI*) of commercial bank deposit concentration for the state in which the borrower operates. *HHI* measures the competition in the local credit market.

3.5. Descriptive statistics

The descriptive statistics for the main variables are shown in Table 2.

We focus on large, publicly listed US firms and over half of the firms in our sample are listed on the NYSE. However, we still see a significant variation in *Firmsize*. The range of bank sizes is even larger, from \$213.2 billion in total assets at the 25th percentile of the distribution to \$1029.1 billion in total assets at the 75th percentile. Therefore, although these banks appear in our sample because a large firm has borrowed from them, they are not exclusively large banks. This variance in bank size allows us to investigate the effect of different bank size on big firm's post-loan outcomes. On average, the post-loan *ROA* is 3.3% and the firm's investment is around 8% of its assets, over the tenor of the loan.

Table 2
Summary statistics.

	n	Mean	25th pctile	Median	75th pctile	Std dev
Dependent variable						
ROA $[t+1,t+n]$	10,204	0.033	0.008	0.039	0.071	0.073
Industry-Adj ROA $[t+1,t+n]$	10,201	0.005	−0.027	0.005	0.042	0.078
Tobins Q $[t+1,t+n]$	9758	1.564	1.099	1.357	1.783	0.714
Investment $[t+1,t+n]$	10,193	0.080	0.035	0.060	0.100	0.069
CAPEX $[t+1,t+n]$	10,193	0.064	0.026	0.045	0.077	0.063
R&D $[t+1,t+n]$	12,217	0.013	0.000	0.000	0.008	0.034
σ(EBIT) $[t+1,t+3]$	8885	0.033	0.010	0.021	0.041	0.036
Asset growth $[t+1,t+n]$	10,183	0.094	−0.006	0.061	0.148	0.193
Employee growth $[t+1,t+n]$	9999	0.046	−0.031	0.020	0.091	0.158
Sale growth $[t+1,t+n]$	10,194	0.097	0.006	0.066	0.149	0.180
Loan characteristics						
Loanspread	12,217	4.916	4.413	5.011	5.521	0.798
Maturity (months)	12,217	49.099	36.000	58.000	60.000	19.083
Collateral	12,217	0.451	0.000	0.000	1.000	0.481
Covenant number	12,217	1.414	0.000	1.333	2.000	1.247
Relationship	12,217	0.728	0.000	1.000	1.000	0.445
Bank characteristics						
Bank asset ($bil)	12,217	684.614	213.194	564.772	1029.062	541.159
Bank size $[t-n,t-1]$	12,217	12.990	12.270	13.244	13.844	1.121
Bank income diversity $[t-n,t-1]$	12,217	0.746	0.679	0.765	0.839	0.123
Bank asset diversity $[t-n,t-1]$	12,217	0.613	0.524	0.625	0.717	0.147
Bank capital $[t-n,t-1]$	12,217	0.075	0.063	0.080	0.092	0.023
Bank operating income $[t-n,t-1]$	12,217	8.172	7.568	8.336	8.900	0.994
Firm characteristics						
Firmsize $[t-n,t-1]$	12,217	6.981	5.792	6.962	8.160	1.746
Leverage $[t-n,t-1]$	12,217	0.248	0.119	0.194	0.347	0.170
Cash $[t-n,t-1]$	12,217	0.095	0.020	0.051	0.122	0.119
Cash flow $[t-n,t-1]$	12,217	0.092	0.057	0.091	0.134	0.078
Market-to-book $[t-n,t-1]$	12,217	2.581	1.395	2.049	3.115	2.521
ROA $[t-n,t-1]$	12,217	0.040	0.013	0.043	0.078	0.075
Tangibility $[t-n,t-1]$	12,217	0.673	0.329	0.596	0.955	0.427
CAPEX $[t-n,t-1]$	12,217	0.077	0.031	0.053	0.090	0.080
Analysts $[t-n,t-1]$	12,217	5.152	0.000	3.433	8.224	5.691
NYSE	12,217	0.575	0.000	1.000	1.000	0.494
Credit dummy	12,217	0.532	0.000	1.000	1.000	0.499
Z score $[t-n,t-1]$	7922	37.740	2.572	4.228	8.546	186.314
State characteristics						
HHI	12,217	0.123	0.055	0.097	0.156	0.100
Coincident index growth	11,905	0.025	0.014	0.029	0.039	0.021
MSA	12,217	0.055	0.000	0.000	0.000	0.229
BRIndex	12,217	1.794	1.300	2.000	2.400	0.765

Table 2 presents the summary statistics of key variables employed in our estimation. We Winsorize all data at the 1st and 99th percentiles.

4. Research design

4.1. Instrumenting Banksize

Evidence suggests (and we verify) that banks and firms match on size, i.e., large firms borrow from large banks and small firms borrow from small banks. To make causal statements regarding the effect of bank size on borrower outcomes we need to minimize the bias arising as a result. Following Berger et al. (2005), we employ an instrumental variables approach to minimize the endogeneity issue.

Instrument relevance:

A good instrumental variable (IV) should have a high correlation with the endogenous regressor (*Banksize*). We instrument *Banksize* with *BRI* which reflects the (borrowing firm's) state's lending environment and therefore affects the firm's choice of bank size. In Section 5.1, we report tests to show that our instrument is strong.

Exclusion restriction:

To be valid, the instrument should have no correlation with the dependent variable (borrower *ROA* or *Investment*) unless through the variables that we explicitly control for. Our instrument, *BRI*, reflects the competition in the banking sector in the (borrowing firm's) state. In order to argue the exogeneity of our instrument with respect to borrower outcomes we briefly discuss below the evolution of bank competition in US states:

Until the early 1970s most US states had intra-state and inter-state branching restrictions, which have gradually been removed over the years. Kroszner and Strahan (1999) relate the origins of the branching restrictions to the generation of revenues by state governments in the form of charter licence fees paid by (locally chartered) banks. Economides et al. (1996) show that for decades, small banks successfully lobbied for stricter branching restriction in order to protect themselves against larger, more efficient banks. Then, in the 1970s and 80s, technological advances made local banking less valuable. Further, the political landscape changed as the Savings and Loans crisis of the 1980s changed the public perception towards the branching restriction laws, since they prohibited the emergence of a more resilient banking sector (Strahan, 2003).

These factors contributed to removing the branching restrictions over time, culminating in the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act, which effectively removes all restrictions on interstate banking at the national level (states were free to implement this law at their own pace). Thus, we argue that competition in the banking sector in the state (both the origins of the restrictions and eventual deregulations) is shaped by power struggles between special interest groups and also the prevailing political landscape. Important for our identification, the deregulations are arguably exogenous to firm-level outcomes.

4.2. 2SLS regression analysis

Our set-up is similar to Dass and Massa (2011). We conduct a cross-sectional analysis at the firm level. We observe the facility level data but if a firm has multiple facilities over a year, we combine the facilities into a single observation for the firm in that year. The dependent variables are the borrower's post-loan outcome, averaged over the tenor of the loan (during $[t+1, t+n]$ years). Firm-level characteristics (averaged over $[t-n, t-1]$ years) are used as controls. t is the start of a loan facility and the n refers to the tenor (or duration) of the facility. The pre-loan average (over $[t-n, t-1]$ years) of the dependent variable is included as a control. As Dass and Massa (and also Delis et al., 2017) point out, the autocorrelation issue that arises in panels when the lagged dependent variable is on the right hand side is eliminated in this set-up because the sampling is event-based. We are not using a true panel, since loan facilities are unique and not repeated in time. Instead we use a cross section of loan facilities across banks and firms.

We employ an instrumental variable two-stage least squares (IV-2SLS) method to minimize the endogeneity in the regressors. In the first-stage, we regress *Banksize* on the instrumental variables and the other firm-level control variables.

$$Banksize_{i,[t-n,t-1]} = \gamma Z_{i,j} + \mu X_{i,[t-n,t-1]} + \alpha + u_{i,[t-n,t-1]}. \quad (2)$$

The vector, $Z_{i,j}$, contains the instrument, *BRI* belonging to the state, j, in which the borrower, i, operates. The fitted value of *Banksize* from the first stage is used in the second stage as the independent variable.

$$DepVar_{i,[t+1,t+n]} = \beta \widehat{Banksize}_{i,[t-n,t-1]} + \theta X_{i,[t-n,t-1]} + \gamma_j + \delta_t + \epsilon_{i,[t-n,t-1]}. \quad (3)$$

The X vector contains the firm level control variables such as *Firmsize*, *Leverage* and others discussed in the previous section. We include industry fixed effects, γ_j using the 12 Fama–French industry classifications (Fama and French, 1997). We include time fixed effects, δ_t which is a dummy for each year in the sample. Finally, we cluster all standard errors at the firm level. All variables are Winsorized at the 1st and 99th percentile to minimize the effect of that outliers.

5. Results

5.1. Instrument relevance

First, we evaluate the relevance of our instrument and appropriateness of the model we use. In Table 3, we present the coefficients on *Firmsize* and the instrument, *BRI* from the first stage of the IV-2SLS[3]. As expected, the sign of the *Firmsize* coefficient is positive and statistically significant, indicating that large firms borrow from large banks. The coefficient on the instrumental variable is significant at the 1% (t-statistic = 4.33) level, implying that the instrument sufficiently predicts the borrower's choice of bank size. The partial F-statistic is 18.7 and significant at the 1% level, so we reject the null hypothesis that the instrument is weak. The Wu-Hausman test (from the second stage) checks whether the OLS and IV-2SLS models give us similar results. We reject the null hypothesis (the F-statistic is 11.8 and significant at the 1% level), indicating that *Banksize* is an endogenous regressor and the IV-2SLS model should be used.

[3] We suppress the other coefficients in the output. Available on request.

Table 3
First stage.

	Banksize
BRIndex	0.036***
	(4.33)
Firmsize	0.098***
	(14.78)
Observations	10,204
Control variables	Yes
Industry, Year fe	Yes
Partial F-test	18.746***
Wu-Hausman	11.829***

This table presents the first stage of the IV-2SLS regression of post-loan firm performance (*ROA*) on *Banksize*. The coefficients of BRIndex and Firmsize are reported in the table and the other control variables are included. *Banksize* is the logarithm of the lender's total assets averaged over $[t-n, t-1]$. All control variables are averaged over $[t-n, t-1]$. Year and industry fixed effects are included. *t-statistics* in parentheses are calculated using heteroskedasticity-robust standard errors clustered on the firm-level identifier. The Partial F-statistic is from the first stage of the IV-2SLS and evaluates the relevance of the instruments. The Wu-Hausman test (from the second stage) checks whether the OLS and IV-2SLS models give us similar results. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

5.2. Value effects

We first present visual evidence (in Fig. 1) that there is a positive relation between Banksize and firm performance. We plot the average post-loan firm ROA for each quartile of Banksize. The average post-loan firm ROA monotonically increases with Banksize and the difference between the two extreme quartiles is 0.019 (t-statistic $= 8.825$). Of course, the visual representation is merely suggestive as we do not control for other factors affecting post-loan performance.

In Table 4, we present the results for our main hypothesis (H1) and examine the effect of bank size on firm performance.

In Column (1), we present our results for our baseline proxy of firm performance, *ROA*. Consistent with our hypothesis, we find that an increase in bank size improves firm value, after adjusting for the selection bias. There is a positive relation between *Banksize* and firm performance, *ROA* and the relationship is statistically significant at the 5% level (coefficient $= 0.083$ and t-statistic $= 2.33$). In terms of economic significance, a 10% increase in bank size leads to an increase in ROA by 0.8%, indicating that firms borrowing from large banks are more profitable, after the origination of the loan. The magnitude of the effect is large; given that the average post-loan *ROA* in our sample is 3.3%, a 0.8% increase in *ROA* is 24% of the mean. These findings lend credence to our hypothesis that large banks add value to their borrowers.

We use two additional proxies for firm value. In Columns (2) and (3), we use the industry-adjusted *ROA* and the *Tobin's Q*, respectively, as a proxy for firm performance. The results are qualitatively unchanged. A 10% increase in bank size increases the post-loan *Tobin's Q* by 8%, which indicates that the market positively views loans from large banks and updates the firm's growth prospects.

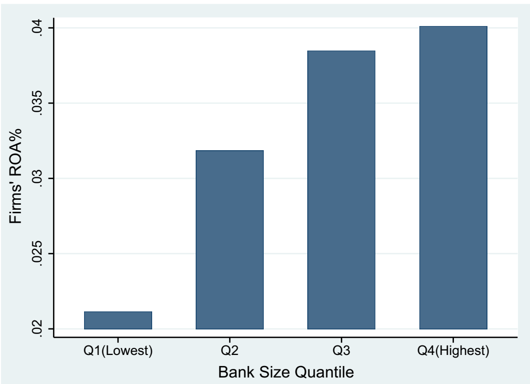

Fig. 1. Average post-loan ROA and bank size quartiles.

Table 4
Bank size and profitability.

	ROA (1)	Industry-Adj ROA (2)	Tobins *Q* (3)
Banksize	0.083**	0.072**	0.801**
	(2.33)	(2.02)	(2.14)
Firmsize	−0.012***	−0.011***	−0.108***
	(−3.26)	(−2.97)	(−2.91)
ROA	0.195***		
	(2.89)		
Industry-Adj ROA		0.383***	
		(8.10)	
TobinsQ			0.523***
			(20.97)
Leverage	0.005	0.009	−0.024
	(0.44)	(0.86)	(−0.21)
Cash	−0.008	−0.006	0.067
	(−0.64)	(−0.52)	(0.55)
Cash flow	0.015	−0.159***	−1.015***
	(0.21)	(−3.21)	(−4.10)
Market-to-book	0.002***	0.002***	
	(3.66)	(4.18)	
Tangibility	0.007	0.009**	0.084**
	(1.61)	(2.32)	(2.36)
CAPEX	−0.070***	−0.038*	−0.513***
	(−3.42)	(−1.89)	(−3.11)
Rel	−0.007**	−0.006*	−0.087***
	(−2.13)	(−1.78)	(−2.62)
Analysts	0.001***	0.001***	0.005**
	(5.19)	(5.04)	(2.12)
NYSE	0.017***	0.017***	0.003
	(6.37)	(6.31)	(0.10)
Credit dummy	−0.006**	−0.007**	0.016
	(−2.34)	(−2.54)	(0.60)
Loanspread	−0.019***	−0.019***	−0.097***
	(−10.48)	(−10.51)	(−5.47)
Maturity	−0.005	−0.005	−0.095**
	(−1.20)	(−1.29)	(−2.25)
Collateral	−0.006**	−0.006**	−0.001
	(−2.27)	(−2.53)	(−0.06)
Covenant number	0.001	0.001	−0.019*
	(0.82)	(0.84)	(−1.76)
HHI	−0.008	−0.012	−0.022
	(−0.90)	(−1.27)	(−0.22)
Bank income diversity	−0.013	−0.006	0.070
	(−1.09)	(−0.56)	(0.64)
Bank asset diversity	−0.071***	−0.063**	−0.621**
	(−2.63)	(−2.34)	(−2.20)
Bank capital	0.669**	0.565**	5.899**
	(2.44)	(2.08)	(2.04)
Bank operating income	−0.043**	−0.037*	−0.435**
	(−2.16)	(−1.88)	(−2.08)
BRI from 1st stage	0.036***	0.036***	0.035***
	(4.33)	(5.28)	(4.92)
Observations	10,204	10,179	9516
Industry, Year fe	Yes	Yes	Yes
Partial *F*-test	18.746***	18.240***	15.927***
Wu-Hausman	11.829***	8.197***	13.034***

This table presents the second stage of the IV-2SLS regression of post-loan firm performance (*Profitability*) on *Banksize*. *Banksize* is the logarithm of the lender's total assets averaged over $[t-n, t-1]$. All control variables are averaged over $[t-n, t-1]$. Year and industry fixed effects are included. t-Statistics in parentheses are calculated using heteroskedasticity-robust standard errors clustered on the firm-level identifier. The BRI from 1st stage is the coefficient of the instrument variable, BRIndex, obtained from the first stage of IV regression. The Partial *F*-Stat is from the first stage of the IV-2SLS and evaluates the relevance of the instruments. The Wu-Hausman test (from the second stage) checks whether the OLS and IV-2SLS models give us similar results. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

In terms of the control variables, the coefficient on *Firmsize* is negative. The coefficient on *Rel* is not significant for the *ROA* measures and is negative and significant for *Tobin's Q*. This indicates that whether or not a firm has an existing relationship with a bank or not does not positively affect its post-loan performance. This is consistent with theory, as we do not expect the firms in our sample to benefit from on-going relationships with banks, due to lower levels of information asymmetry and access to alternate sources of funding. Predictably, stricter loan terms such as a higher interest spread on loans and higher collateral requirements, are negatively associated with firm performance. Bank characteristics are also statistically important.

5.3. Investment effects

In this section, we examine the investment effects of *Banksize* (H2). First, we examine the effect of *Banksize* on the level of investment and firm risk-taking in Table 5.

In Columns (1)–(3), we examine how *Banksize* affects the level of firm investment. An increase in *Banksize* is associated with an increase in the level of post-loan *Investment* (sum of capital expenditure and *R&D* spending). In terms of economic magnitude, a 10% increase in *Banksize* is associated with a 0.5% increase in the level of investment. The result also holds for each component of *Investment* (*CAPEX* and *R&D* spending), separately.

In Column (4), we examine how *Banksize* affects the volatility of earnings, $\sigma(EBIT)$, which is our proxy for firm risk-taking. An increase in *Banksize* increases the volatility of *EBIT* (the coefficient on *Banksize* is positive and significant at 10%). This result is consistent with the findings above that firms increase their level of investment.

How does a higher level of investment affect a firm's growth rate? We check this in Table 6.

Consistent with the observed investment effects, there is a positive relation between *Banksize* and a firm's growth rate. A 10% increase in *Banksize* increases the post-loan growth rate of firms by around 2.2% (in terms of firms assets). The coefficient on *Banksize* is positive for three proxies that we use but only statistically significant for the asset and sales proxies.

This ties in well with our main results that firm performance increases with *Banksize* and sheds light on one of the channels driving our main findings: it appears that an increase in bank size allows firms to invest more and take more risk. This results in a faster growth rate in firms and ultimately, higher value for the borrower.

5.4. Effects across different types of firms

In this section, we test our final hypothesis that the observed effects will be mainly concentrated in firms that are ex-ante safer (H3).

In Table 7, we split up firms into low (safe) and high (risky) leverage subsets. We report the coefficient on *Banksize* for each dependent variable.

While the value effects are positive for both subsets sorted by ex-ante firm leverage, the effects are stronger (bigger magnitude) and statistically significant only in the low leverage (safe) subset of firms. Specifically, in the low leverage sub-sample, a 10% increase in *Banksize* leads to an increase in *ROA* by 2%, which is more than double the magnitude of the effect in the full sample.

Next, we turn to the investment effects. In the low leverage sub-sample, the effect of *Banksize* is positive and significant for all three proxies of investment. However, in the high leverage sub-sample, the coefficient on *Banksize* in any of the investment regressions is not statistically significant. This suggests that investment increases with *Banksize* only in the low leverage (safer) sub-sample.

Similarly, in Table 8, we split up firms into low (risky) and high (safe) *Z*-score subsets. We report the coefficient on *Banksize* for each dependent variable.

The value effect is positive and statistically significant in the high *Z*-score(safe) sub-sample only; it is still positive, but statistically insignificant in the low *Z*-score firms. The investment effects also concentrate only in the high *Z*-score firms. *Banksize* is positively and statistically significantly (5% level) related to earnings volatility in the high *Z*-score firms; it is negative, but not statistically significant in the low *Z*-score firms.

Overall, consistent with our predictions, the above results indicate that large banks add value to the ex-ante safe borrowers by encouraging (or allowing) them to invest more and take more risk. For riskier firms, whose risk taking is likely above the optimal level, the investment effects are muted or absent and the value effects are neutral. Importantly, the value effect of *Banksize* for the riskier firms is not negative.

6. Robustness

6.1. Instrument variation

In the baseline, we take the time-weighted average BRI over the sample period as this reflects the intensity at which state regulators removed restrictions. In this section, we add more variation to our instrument by making it time varying at the state level (e.g., Nguyen et al., 2017). Additionally, we cluster the errors at the state-year level to account for any common element to the regression errors across the firms operating in the same state[4]. We show the results in Table 9 and report the coefficient on *Banksize* for each dependent variable.

[4] The results remain qualitatively unaffected compared to the case when we cluster the errors at the firm-level.

Table 5
Bank size, investment and risk.

	Investment (1)	*CAPEX* (2)	*R&D* (3)	σ(*EBIT*) (4)
Banksize	0.053**	0.046*	0.019*	0.023*
	(1.99)	(1.94)	(1.84)	(1.71)
Firmsize	−0.009***	−0.008***	−0.002**	−0.005***
	(−3.18)	(−3.15)	(−2.01)	(−3.84)
Investment	0.389***			
	(18.77)			
CAPEX		0.303***		
		(12.56)		
R&D			0.602***	
			(25.92)	
σ(EBIT)				0.147***
				(6.77)
ROA	−0.214***	−0.216***	0.012	−0.014
	(−4.25)	(−4.69)	(1.01)	(−0.56)
Leverage	−0.013	−0.002	−0.004*	−0.017***
	(−1.49)	(−0.26)	(−1.79)	(−3.80)
Cash	0.021**	−0.008	0.008**	0.019***
	(2.44)	(−1.19)	(2.01)	(3.77)
Cash flow	0.147***	0.202***	−0.036***	0.019
	(2.83)	(4.19)	(−2.65)	(0.73)
Market-to-book	0.000	−0.000	0.000	0.000
	(1.11)	(−0.57)	(0.27)	(1.14)
Tangibility	0.020***	0.028***	0.001	0.003
	(5.72)	(7.95)	(1.47)	(1.44)
Rel	−0.009***	−0.006***	−0.002**	−0.003*
	(−3.64)	(−2.86)	(−2.46)	(−1.90)
Analysts	0.000	0.000	0.000***	−0.000
	(1.19)	(0.44)	(4.21)	(−1.25)
NYSE	−0.000	0.001	0.000	−0.001
	(−0.24)	(0.39)	(0.08)	(−0.58)
Credit dummy	0.000	0.000	−0.001	−0.001
	(0.17)	(0.08)	(−1.13)	(−0.67)
Loanspread	−0.006***	−0.004***	−0.002***	0.003***
	(−4.29)	(−3.82)	(−4.10)	(3.28)
Maturity	−0.011***	−0.008***	−0.005***	−0.003**
	(−3.65)	(−2.80)	(−3.24)	(−2.49)
Collateral	0.001	0.002	0.001	0.004***
	(0.49)	(0.98)	(1.52)	(3.60)
Covenant number	−0.003***	−0.002***	0.000	−0.002***
	(−3.17)	(−2.74)	(0.64)	(−4.74)
HHI	−0.001	−0.011*	0.007***	−0.005
	(−0.07)	(−1.65)	(2.63)	(−1.11)
Bank income diversity	−0.003	−0.001	−0.002	0.000
	(−0.36)	(−0.17)	(−0.69)	(0.04)
Bank asset diversity	−0.034*	−0.032*	−0.008	−0.014
	(−1.74)	(−1.90)	(−1.09)	(−1.40)
Bank capital	0.388*	0.331*	0.158*	0.159
	(1.89)	(1.81)	(1.87)	(1.51)
Bank operating income	−0.032**	−0.027**	−0.011**	−0.013*
	(−2.13)	(−2.02)	(−1.96)	(−1.79)
BRI from 1st stage	0.034***	0.034***	0.030***	0.041***
	(5.00)	(4.95)	(4.82)	(5.54)
Observations	10,193	10,193	12,217	8352
Industry, time fe	Yes	Yes	Yes	Yes
Partial *F*-test	16.348***	16.043***	15.329***	20.917***
Wu-Hausman	9.039***	8.002**	6.090**	4.735**

This table presents the second-stage results of the IV-2SLS regressions of firm investment on *Banksize*. The dependent variables are defined as the borrower's *Investment* (Column (1)), *CAPEX* (Column (2)), *R&D* spending (Column (3)) or σ(EBIT) (Column (4)), averaged over $[t+1, t+n]$. The main independent variable, *Banksize*, is the logarithm of the lender's total assets averaged over $[t-n, t-1]$. All control variables are averaged over $[t-n, t-1]$. Year and industry fixed effects are included. *t*-Statistics in parentheses are calculated using heteroskedasticity-robust standard errors clustered at the firm level. The BRI from 1st stage is the coefficient of the instrument variable, BRIndex, obtained from the first stage of the IV regression. The Partial *F*-statistic is from the first stage of the IV-2SLS and evaluates the relevance of the instruments. The Wu-Hausman test (from the second stage) checks whether the OLS and IV-2SLS models give us similar results. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

The results remain generally consistent with the baseline. The value effects are economically of similar magnitude as the baseline and are statistically stronger (all three proxies are statistically significant at the 1% level). In terms of the investment effects, *Investment* and *CAPEX* are positive and statistically significant at the 10% level. *R&D* spending and the risk proxy σ(*EBIT*) are still positive, but are no longer statistically significant.

Table 6
Bank size and firm growth rate.

	Assets (1)	*Employees* (2)	*Sales* (3)
Banksize	0.218**	0.104	0.161*
	(2.05)	(1.32)	(1.67)
Firmsize	−0.045***	−0.031***	−0.040***
	(−4.10)	(−3.70)	(−3.95)
ROA	0.137	0.108	0.260**
	(1.05)	(1.10)	(2.17)
Leverage	−0.012	0.017	−0.001
	(−0.40)	(0.74)	(−0.03)
Cash	0.045	0.062***	0.121***
	(1.59)	(2.89)	(4.74)
Cash flow	−0.106	−0.037	−0.327**
	(−0.77)	(−0.34)	(−2.37)
Market-to-book	0.003***	0.002**	0.002**
	(3.03)	(2.13)	(2.08)
Tangibility	0.010	−0.021**	0.010
	(0.86)	(−2.25)	(0.85)
CAPEX	0.045	0.129***	0.119**
	(0.92)	(3.07)	(2.38)
Rel	−0.006	−0.000	−0.005
	(−0.61)	(−0.01)	(−0.59)
Analysts	0.001*	0.001*	0.001*
	(1.91)	(1.65)	(1.91)
NYSE	0.025***	0.015***	0.022***
	(3.32)	(2.82)	(3.30)
Credit dummy	−0.012	−0.002	−0.002
	(−1.63)	(−0.45)	(−0.36)
Loanspread	−0.018***	−0.011***	−0.007*
	(−3.64)	(−2.95)	(−1.65)
Maturity	−0.023**	−0.012	−0.023**
	(−1.99)	(−1.35)	(−2.08)
Collateral	0.008	0.005	0.009
	(1.03)	(1.03)	(1.39)
Covenant number	−0.005	−0.002	−0.004
	(−1.55)	(−0.66)	(−1.21)
HHI	−0.004	0.003	−0.030
	(−0.11)	(0.14)	(−1.13)
Bank income diversity	−0.024	−0.059**	−0.057**
	(−0.79)	(−2.49)	(−1.97)
Bank asset diversity	−0.158**	−0.061	−0.084
	(−2.02)	(−1.10)	(−1.23)
Bank capital	1.619**	0.687	1.169
	(2.02)	(1.17)	(1.60)
Bank operating income	−0.126**	−0.062	−0.097*
	(−2.10)	(−1.41)	(−1.80)
BRI from 1st stage	0.034***	0.034***	0.034***
	(5.08)	(5.07)	(5.06)
Observations	10,183	9999	10,194
Industry, time fe	Yes	Yes	Yes
Partial *F*-test	16.909***	16.866***	16.781***
Wu-Hausman	8.362***	2.919*	5.109**

This table presents the second-stage results of the IV-2SLS regressions of firm growth rates on *Banksize*. The dependent variables are defined as the borrower's asset growth rate (Column (1)), employee growth rate (Column (2)) or sales growth rate (Column (3)), averaged over $[t+1, t+n]$. The main independent variable, *Banksize*, is the logarithm of lender's total assets averaged over $[t-n, t-1]$. All control variables are averaged over $[t-n, t-1]$. Year and industry fixed effects are included. *t*-Statistics in parentheses are calculated using heteroskedasticity-robust standard errors clustered at the firm level. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

6.2. Geographical factors

There is evidence that bank lending varies significantly across US states (Benmelech et al., 2017). It would be problematic to interpret our results if firms of a certain size are clustered in certain states. Rice and Strahan (2010) find that there is no correlation between the structure of the non-banking industry (share of small firms) and the deregulation index. Specifically, they find that the correlation between the share of small firms in the state and the branching deregulation index is .16 and is not statistically significant

Table 7
Sub-samples based on leverage ratio.

Dependent Var	Low leverage (1)	High leverage (2)
ROA	0.207**	0.008
	(2.17)	(0.19)
IndustryAdj ROA	0.190**	−0.007
	(2.20)	(−0.16)
TobinsQ	2.225*	0.228
	(1.90)	(0.65)
Investment	0.128*	0.015
	(1.87)	(0.50)
CAPEX	0.103*	0.022
	(1.80)	(0.75)
R&D	0.052*	−0.001
	(1.65)	(−0.06)
$\sigma(EBIT)$	0.036	0.015
	(1.53)	(0.76)

This table presents a summary of the second stage results when we divide the sample into two subsamples based on the leverage ratios of borrowers. In each column we show the second stage coefficients on *Banksize* for each dependent variable. In Column (1), the leverage ratios of the borrowers are lower than the median value (0.19) of the whole sample. In Column (2), the leverage ratios of the borrowers are relatively higher (above 0.19). Year and industry fixed effects are included and standard errors are clustered at the firm level. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

Table 8
Sub-samples based on *Z*-score.

Dependent Var	Low *Z*-score (1)	High *Z*-score (2)
ROA	0.176	0.103**
	(0.62)	(2.10)
IndustryAdj ROA	0.124	0.094*
	(0.51)	(1.90)
TobinsQ	1.545	0.718
	(0.62)	(1.40)
Investment	0.017	0.059**
	(0.16)	(2.10)
CAPEX	0.053	0.035
	(0.50)	(1.52)
R&D	0.011	0.027*
	(0.28)	(1.90)
$\sigma(EBIT)$	−0.046	0.045**
	(−0.45)	(2.15)

This table presents a summary of the second stage results when we divide the sample into two subsamples based on *Z*-score. In each column we show the second stage coefficients on *Banksize* for each dependent variable. In Column (1), we include the firms with low *Z*-score. In Column (2), we include the firms with high *Z*-score. Year and industry fixed effects are included and standard errors are clustered at the firm level. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

However, there are many other state specific factors that may affect both the demand and supply of credit. Below, we examine the possibility that state-specific macroeconomic factors may influence the value and investment effects of *Banksize*. We show the results in Table 10 and report the coefficients on *Banksize* for each dependent variable.

First, in Column (1), we include the growth rate in the Coincident index for the state in which the borrower is headquartered.[5] By including the growth rate in the Coincident index in the regressions, we controls for the state's macroeconomic conditions. The coefficients on *Banksize* for all dependent variables remain positive and statistically significant.

Next, we augment the model by interacting *Banksize* with the growth rate in the state Coincident index. In addition to the coefficient on *Banksize* (Column (2)), we report the coefficient on the interaction term in Column (3). The stand-alone effect

[5] The Coincident index combine four state-level indicators including non-farm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and wage and salary disbursements deflated by the Consumer Price Index. The trend for each state's index is set to the trend of its Gross Domestic Product (GDP), so long-term growth in the state's index matches the long-term growth in its GDP.

Table 9
Time-varying BRI.

Dependent Var	Time-varying BRI
ROA	0.088***
	(2.82)
IndustryAdj ROA	0.082***
	(2.59)
TobinsQ	0.738***
	(2.65)
Investment	0.035*
	(1.73)
CAPEX	0.032*
	(1.79)
R&D	0.011
	(1.32)
$\sigma(EBIT)$	0.008
	(0.69)

This table presents a summary of the second stage results when using the time-varying BRI as the instrument variable. In each column we show the second stage coefficients on *Banksize* for each dependent variable. Year and industry fixed effects are included and standard errors are clustered at the state-year level. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

of *Banksize* on each dependent variable remains positive and statistically significant. Importantly, the interaction term is not statistically significant for any of the dependent variables. This indicates that the value and investment effects of *Banksize* do not vary with state-specific macroeconomic conditions.

In Column (4), we use the time-varying version of the instrument and include state fixed effects (in addition to the industry and time fixed effects). The value effects are still consistent (positive and statistically significant at 5% or 10%). The investment effects lose statistical power. Our instrument is at the state-year level and for the majority of the states the instrument does not vary much over time, e.g., for Alaska, the index equals 2 from 1994 to 2009, when it is set equal to 0 due to the Dodd-Frank Act. This implies that the state fixed effects and our instrument are highly correlated. Therefore, including state fixed effects in the regressions removes most of the variation from the instrument. Hence, when we add the state fixed effects, some of our results are no longer consistent.

Finally, we test whether geographic proximity between the bank and the borrower affects our results. Following Dell'Ariccia et al. (2017), we construct a dummy variable, *MSA*, which equals 1 if the borrower borrows from at least one bank operating in the same Metropolitan Statistical Area and 0, otherwise. We use the zip codes provided by DealScan and the link table between zip codes and Core Based Statistical Areas sourced from the USA CSBA Database to identify the MSA in which the borrower and lenders are located.

We augment the baseline by including the *MSA* dummy and its interaction with *Banksize*. In addition to the coefficient on *Banksize* (Column (5)), we report the coefficient on the interaction term in Column (6). Both value and investment effects are positive and statistically significant (only $\sigma(EBIT)$ is marginally insignificant with a t-statistic of 1.61). The interaction term is consistently insignificant for all dependent variables. This indicates that geographic proximity between the borrower and lender does not explain the relationship between *Banksize* and borrower outcomes.

6.3. Further robustness

In Table 11, we present some additional robustness tests. We report the coefficient on *Banksize* for each dependent variable.

In Column (1), we report the results for the period 2000–2010, following Delis et al. (2017). This is to avoid the effects arising from regulatory reforms before 2000 (Gramm-Leach-Bliley Act of 1999 and other earlier ones) and in 2010 (Dodd-Frank Act of 2010). All coefficients are consistent with the baseline. In terms of statistical significance, the value effects are strong. *CAPEX* increases with *Banksize* (statistically significant at 5%), but the effect of *Banksize* on *R&D* spending and the risk proxy are no longer statistically significant.

In Column (2), instead of taking the average size of the banks in the syndicate, we use the size of the largest bank in the syndicate as our measure of *Banksize*. All coefficients remain consistent with the baseline and are statistically significant. Finally, in Column (3), instead of taking the averages over the tenor of the loan, we use the firm outcomes in the year after the loan origination as the dependent variable and the firm controls are lagged by one year. Essentially, in our IV-2SLS regressions, we replace the subscript, n with 1. The results remain qualitatively robust.

7. Conclusion

We examine the effect of bank size on borrower outcomes, when information asymmetry problems are not severe. We focus on large, publicly traded firms, which is an important departure from the soft information literature. Using a sample of 20,806

Table 10
Geographical variation.

Dependent Var	SCI	SCI interaction		State FE	Same MSA	
		Banksize	Interaction		Banksize	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)
ROA	0.091**	0.096**	0.378	0.106**	0.079**	0.004
	(2.41)	(2.35)	(0.58)	(2.03)	(2.14)	(0.06)
IndustryAdj ROA	0.078**	0.082**	0.376	0.120**	0.061*	−0.033
	(2.11)	(2.06)	(0.60)	(2.12)	(1.68)	(−0.46)
TobinsQ	0.829**	0.853**	1.498	0.771*	0.824**	0.123
	(2.18)	(2.14)	(0.29)	(1.71)	(2.05)	(0.31)
Investment	0.056**	0.066**	0.599	0.002	0.062**	0.045
	(2.05)	(2.03)	(1.18)	(0.07)	(2.12)	(0.98)
CAPEX	0.048**	0.059*	0.589	0.003	0.054**	0.037
	(1.98)	(1.96)	(1.23)	(0.09)	(2.08)	(0.94)
R&D	0.019*	0.022*	0.187	−0.004	0.020*	0.006
	(1.78)	(1.73)	(1.08)	(−0.29)	(1.80)	(0.62)
σ(*EBIT*)	0.026*	0.027*	0.157	−0.017	0.022	−0.012
	(1.86)	(1.86)	(0.48)	(−0.64)	(1.61)	(−0.42)

This table presents a summary of the second stage results when considering the geographical variation of the loans. In each column we show the second stage coefficients on *Banksize* for each dependent variable. In Column (1), we add *State Coincident Index* (SCI) as one of the control variables to control for the macroeconomic conditions of the state. Next, we interact *Banksize* with the growth rate in the state Coincident index (*SCI*) and report the coefficients of *Banksize* and *Banksize**SCI* in Columns (2) and (3), respectively. In Column (4), we use the time-varying BRI as the instrument variable and include the state-level fixed effects. Finally, we interact *Banksize* with MSA that equals 1 if the borrower borrows from at least one bank operating within the same MSA in a given year and 0 otherwise. We report the coefficients of *Banksize* and *Banksize**MSA* in Column (5) and (6), respectively. Year and industry fixed effects are included. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

loan facilities granted to 3625 publicly traded US companies between 1992 and 2015, we find that there is a positive relation between bank size and firm value, after minimizing the potential selection bias. Firms that borrow from large banks invest more. These firms have higher earnings volatility and grow faster. The effects are concentrated in borrowers that are ex-ante (pre-loan) safer. The effects are muted in riskier firms, and are still positive, but not statistically significant.

Our results have important policy implications. There is ample evidence with regards to the negative costs that large banks impose on the system. Politicians and central bankers have called for the break up of large banks to limit these costs. We find evidence that large banks are able to add value when lending to large, publicly traded firms. We highlight the bright side of bank size, which presents the regulator with a trade-off in determining the optimal bank size.

Table 11
Further robustness.

Dependent Var	Keep 2000–2010 (1)	Largest (2)	Lagged (3)
ROA	0.084**	0.065**	0.068*
	(2.46)	(2.38)	(1.72)
IndustryAdj ROA	0.078**	0.056**	0.073*
	(2.29)	(2.08)	(1.74)
TobinsQ	0.606*	0.628**	0.419
	(1.92)	(2.22)	(1.42)
Investment	0.046**	0.037*	0.084**
	(2.18)	(1.87)	(2.50)
CAPEX	0.043**	0.033*	0.076**
	(2.27)	(1.86)	(2.46)
R&D	0.010	0.014*	0.015
	(1.09)	(1.70)	(1.55)
σ(*EBIT*)	0.018	0.017*	0.040
	(1.36)	(1.66)	(1.44)

This table presents a summary of the second stage results when using different samples. In each column we show the second stage coefficients on *Banksize* for each dependent variable. In Column (1), we report the results for the period 2000–2010, following Delis et al. (2017) . In Column (2), instead of taking the average size of the banks in the syndicate, we use the size of the largest bank in the syndicate as our measure of *Banksize*. Finally, in Column (3), instead of taking the averages over the tenor of the loan, we use the firm outcomes in the year after the loan origination as the dependent variable and the firm controls are lagged by one year. Year and industry fixed effects are included and standard errors are clustered at the firm level. *, ** and *** represent significance at 10%, 5% and 1%, respectively.

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