Intangible Investments and the Persistent Effect of Financial Crises on Output*

Maarten De Ridder‡
University of Cambridge

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Abstract

This paper empirically identifies a mechanism through which financial crises exert persistently negative effects on output. Endogenous growth theory suggests that a shortfall in intangible investments temporarily slows technological progress, creating a gap between pre-crisis trend and actual GDP. I test this hypothesis using a linked lender-borrower dataset on 522 U.S. corporations responsible for 58% of industrial research and development. Exploiting variation in firm-level exposure to the Global Financial Crisis, I show that tight credit conditions reduced intangible investments even for large corporations, and significantly slowed down revenue growth between 2010 and 2015. When jointly estimating the response of revenue and patents to intangible investments, capital investments and changes in employment during the crisis, I find that only intangible investments have a persistently negative effect.

Keywords: Financial Crises, Endogenous Growth, Innovation, Firms
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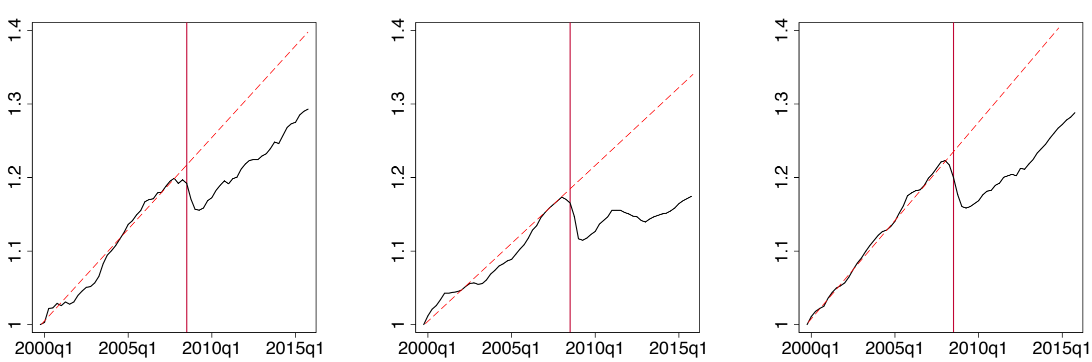
‡*Address:* University of Cambridge, Faculty of Economics, Sidgwick Ave, Cambridge, CB3 9DD, U.K. *E-mail*: mcd58@cam.ac.uk. *Web:* http://www.maartenderidder.com/.

1. Introduction

Recovery from the Global Financial Crisis of 2007-2008 and the ensuing "Great Recession" was weak. In the United States, GDP deviated 10% from the level that an extrapolated trend between 2000 and 2007 predicts. Similar deviations are observed across developed economies, as Figure 1 illustrates.[1] This is at odds with business cycle models, in which output recovers to its original trend after a transitory shock. In endogenous growth models, however, a one-time reduction in intangible investments - such as research and development - can have a persistent effect on output. Such a drop temporarily slows the rate of technological progress below the balanced growth path. When the crisis fades and investments recover, technological progress regains its original growth rate. The level of GDP does not recover from losses during the crisis, however, and remains on a lower trajectory (e.g. Anzoategui et al. 2019, Ikeda and Kurozumi 2019, Queraltó 2019).

An alternative hypothesis is that the lack of recovery from the Global Financial Crisis was driven by secular factors. In particular, the crisis coincided with a slowdown in the growth rate of productivity, which commenced around 2005. Since that year, productivity growth in the United States has averaged less than 0.5%, well below the long-term average of 1.5% (Fernald 2014).[2] Fernald et al. (2017) use time-series tests to show that the growth rate of total factor productivity has a structural break around 2006, and conclude that the productivity slowdown was, therefore, not a consequence of the crisis. An analysis of structural breaks cannot preclude, however, that the crisis worsened the productivity slowdown through the endogenous growth channel, especially as the crisis commenced shortly after the structural break. Micro-level evidence of intangible investments and medium-term growth can be used to assess whether this is the case.

Figure 1. Real Gross Domestic Product versus Trend, 2000-2015



(a) United States (b) Euro Area (c) United Kingdom

Solid and dashed lines present actual and trend (log) GDP, respectively. Series are standardized such that 2000Q1 has value 1. Vertical-red line indicates quarter of Lehman Brother's failure. Trends extrapolate growth rate between 2000 and 2007. Data: OECD.

[1] This is illustrative of the general lack of recovery after systemic banking crises. Based on 117 crises between 1960 and 2001, Cerra and Saxena (2008) show that output on average remains 7% below trend a decade after a crisis. Similar evidence is found in, e.g., Furceri and Zdzienicka (2012), Reinhart and Rogoff (2014), and Teulings and Zubanov (2014).

[2] A similar slowdown is visible across the majority of advanced economies. See Adler et al. (2017) for a review.

This paper provides such evidence for a sample of 522 medium- to large-sized firms in the United States, responsible for 58% of corporate research and development. I show that the crisis reduced these firms' intangible investments and persistently affected their revenue. The analysis relies on the shift-share approach (e.g. Borusyak et al. 2019, Goldsmith-Pinkham et al. 2019), in the sense that the effect of the crisis is identified using firm-level variation in the degree of exposure to tight credit. I measure exposure to tight credit in two ways. First, I follow Chodorow-Reich (2014) by exploiting the long-term nature of relationships between firms and banks to measure exposure to the crisis through the health of banks that firms borrowed from prior to the crisis.[3] Firms that rely on loans from banks that were highly exposed to Lehman Brothers' bankruptcy, asset-backed securities, or interbank markets face greater difficulty and costs when obtaining credit during the Global Financial Crisis. Second, I measure exposure to the crisis through the fraction of a firm's long-term debt that is due at the onset of the crisis. These firms face higher refinancing risk, which reduces the optimal quantity of intangible investments directly if financed by credit, or indirectly if firms prioritize short-term capital investments (Garicano and Steinwender 2016).

I find that firms with greater exposure to the Global Financial Crisis experience persistent declines in revenues. The estimated effect is large: revenue is, on average, between 3 and 10 percent lower by 2015 for each standard deviation of crisis exposure. I then explore whether the persistent effect on revenues is driven by a decline in intangible investments as predicted by endogenous growth theory, in two steps. First, I show that firms with greater exposure to the crisis reduce investments in research and development (R&D). While R&D does not encompass the universe of intangible investments, it is directly observable on the income statement of U.S. firms and is a standard measure in the innovation literature (e.g., Hall et al. 2010). Measured as a percentage of the stock of past R&D, firms reduce their investments by 0.5 to 1.2 percentage points during the crisis per standard deviation of exposure, though significance depends on the measure considered. Second, I show that intangible investments during the crisis are more likely to drive the crisis' persistent effect on revenues than employment and capital investments. To do so, I instrument intangible investments, capital investments, and employment growth during the crisis with the firm-level crisis exposure. I then show that only instrumented intangible investments significantly correlate with medium-term revenue growth in a joint estimation. This result holds in dynamic regressions with various exposure measures, firm, and sector-year fixed effects.

The causal interpretation of these results hinges on two conditions. The first part of the analysis, showing that crisis-exposed firms face persistent losses to revenue, requires that exposure to the crisis does not correlate with unobserved determinants of the path of revenue absent the crisis.[4] To assess whether this condition is satisfied I deploy the common strategy of comparing the balance of observable covariates and pre-trends. I find that firms with higher exposure to the cri-

[3] By analyzing the effect of shocks to intangible investments on within-firm growth, this paper does not test the effect of resource allocation (e.g. Gopinath et al. 2017) or entry and exit (e.g. Clementi and Palazzo, 2016).

[4] This would be violated, for example, if banks with high exposure to asset-backed securities or Lehman Brothers' failure lent to firms with particularly risky investments. Similarly, if having a large fraction of debt mature at the onset of the crisis reflects poor managerial skills, this would also affect revenue growth.

sis operate in similar sectors, are based in similar states, initially grow at similar rates and have similar intangible investments, leverage, and profitability, though exposed firms are slightly older and larger. Pre-crisis trends on these variables are also similar. This supports causal interpretation under the assumption that unobservable confounders are correlated with observables (e.g. Oster 2019). Importantly, firms with high and low exposure also have similar book-to-market and price-earnings ratios, which suggests that financial markets expected their future profitability and growth to be similar. I furthermore show that links between firms and banks are quasi-random, because the predicted decline in new loans from exposed banks to specific borrowers does not depend on the inclusion of borrower fixed effects (Khwaja and Mian 2008).

The second condition is the exclusion restriction, which is relevant for the analysis of the effect of intangible investments on post-crisis revenue growth. This effect warrants a causal interpretation if exposure to the financial crisis does not affect revenue growth through channels that I do not control for. It is likely that my measure of intangible investments (R&D) does not capture the entirety of channels, as other innovative investments can also affect revenue persistently. The analysis does control, however, for capital investments and changes to employment during the crisis. As intangible investments are the only predictor of medium-term revenue growth, my results do imply that these investments - and innovative investments that correlate positively with it - are more likely to drive the crisis' persistent effect than employment cuts and capital investments.

To provide further evidence on the role of intangible investments in the lack of recovery, I look at the innovation output of firms that were exposed to the crisis. I measure innovation through the market value of successful patent applications, based on abnormal stock market returns around announcement days. Results show that the total value of patents awarded to firms with greater exposure to the crisis is 10 to 20 percent lower per standard deviation of exposure. The effect becomes significant around 5 years after the crisis, which implies a plausible lag in the effect of crisis-induced reductions in innovative investments on innovation output. The lag is furthermore similar to the lag in the response of firm revenues. When estimating the medium-term effects of intangible investments in a regression with controls for employment, capital investment, firm and sector-year fixed effects, I again find that only intangible investments explain the lack of patents. These results corroborate the endogenous growth hypothesis that this paper scrutinizes.

Related Literature The paper relates most closely to Huber (2018), who assesses the impact of lending cuts by a large German bank and finds persistent effects on firm-size and productivity. I show that the negative effect of exposure increases over time for a horizon twice as long as Huber's, and show this for large firms in the United States. To my knowledge, this paper is also the first to show that intangible investments form the most plausible channel through which this persistence operates, rather than reductions in employment and capital. Subsequent papers also exploit a shift-share design to explain persistent effects of the Global Financial Crisis. Duval et al. (2019) show that a sample of European firms with high pre-crisis leverage faced lower growth of revenue productivity after the crisis.[5] Dörr et al. (2018) and Manaresi and Pierri (2018) show that credit affects productivity of Italian firms, while Linarello et al. (2019) find positive effects on reallocation.

More broadly, my empirical strategy builds on papers that use firm-exposure to lending shocks to assess the real effects of financial crises. Relevant examples include Chodorow-Reich (2014), Acharya et al. (2018), Bentolila et al. (2017) and Giroud and Mueller (2017), who analyze the employment effects of credit shocks using firm-level crisis exposure. Franklin et al. (2015) conduct a similar exercise for the United Kingdom, and add that tight credit negatively affected labor productivity in 2008-9. It is similarly related to Amiti and Weinstein (2011), Almeida et al. (2012), Greenstone et al. (2019), Adelino et al. (2015), Aghion et al. (2017), Paravisini et al. (2015). These papers use exposure to credit shocks to analyze the effect on investments, exports and short-term output.

This paper primarily contributes empirical evidence to the theoretical literature that aims to explain the persistent effects of financial crises through endogenous growth. Aghion et al. (2010) shows that liquidity shocks move firms away from long-term intangible investments in favour of short-run production capital.[6] Garcia-Macia (2017) adds that firms are unable to fund investment in intangible assets during financial crises, as these investments are hard to collateralize. The models in Ates and Saffie (2013, 2014) imply that financial turmoil affects technological progress through the ability of banks to observe project quality under imperfect information. In Queraltó (2019), financial crises increase the costs of financial intermediation, which reduces the entrance of entrepreneurs that need to fund entry costs. Similar mechanisms are described in a New Keynesian framework by Garga and Singh (2016) and in the context of the zero lower bound by Moran and Queralto (2018). Schmitz (2014) adds that crises particularly affect small and young firms, which produce more radical innovations. Crises may also reduce the profitability of intangible investments and innovation because demand and prices are low, as suggested by Fatas (2000), Ikeda and Kurozumi (2019), Bianchi et al. (2019), Benigno and Fornaro (2017) and Anzoategui et al. (2019). Results in this paper suggest that tight credit explains the lack of intangible investments, though low demand could form a complementary channel.

This paper's second contribution is the finding that intangible investments are affected by external finance. The conventional wisdom is that firms prefer to finance such investments internally using cash flow or equity (Hall and Lerner 2010, Brown et al. 2009). This paper is in line with a growing literature that does find an effect of bank lending on R&D. For the Great Depression, Nanda and Nicholas (2014) show that firms which operated in counties where banks were hit by the crisis applied for fewer and less-well cited patents in following years. An emerging literature, surveyed by Nanda and Kerr (2015), furthermore finds that bank deregulation during the 1980s benefited innovation. For the 2008-9 financial crisis, Kipar (2011) shows that German firms that borrowed from credit unions rather than commercial banks were more likely to cancel innovative projects. Gari-

[5] While the number of observations in those papers is larger, firms in this paper are responsible for a greater share of global corporate R&D. This paper's firms are responsible for 58% of U.S. corporate R&D in 2007, which exceeds the sum of corporate R&D undertaken in the entire European Union that year by 21%.

[6] Empirical support for this mechanism based on French micro data is provided in Aghion et al. (2012).

cano and Steinwender (2016) show that crises change the composition of investments of Spanish firms towards short instead of long-term capital. My result suggests similar mechanisms apply for the U.S. in a sample of for medium- to large-sized firms with access to bond markets. This might be because bonds and bank loans are imperfect substitutes (Crouzet, 2017; Xiao, 2018), or because the costs of issuing bonds during the crisis were high (Goel and Zemel, 2018).[7]

Outline The remainder of this paper proceeds follows. The dataset and the main variables for the analysis are discussed in Section 2. Measures of exposure to the Global Financial Crisis as well as analyses on the effect of exposure on medium-term revenue and patents are presented in Section 3. The effect of exposure on intangible investments is analyzed in Section 4, Section 5 concludes.

2. Data

2.1. Construction

The analysis relies on firm-level data from Compustat. Compustat contains the balance sheet and income statement of the universe of U.S. publicly listed firms and is used to obtain firm variables for investments, output growth and covariates. I keep firms that engage in R&D at least once in the three years prior to the crisis and drop firms with missing or negative assets and sales, as well as firms that enter the dataset after 2003 or exit before 2015.[8] Firms in finance, insurance and real estate (FIRE), as well as firms in regulated utility sectors are excluded. All variables are deflated to 2009 USD using the BEA's GDP deflator and tails are winsorized for the bottom and top 15 firms. Stock and market capitalization data is obtained by merging the resulting dataset with CSRP.

I obtain the names of banks that these firms borrow from DealScan. DealScan covers the near universe of syndicated loans in the United States and contains loan-level identifiers of lenders and borrowers.[9] This allows me to calculate firm-level measures of exposure to tight credit during the Global Financial Crisis, based on the health of the banks that firms borrowed from prior to the crisis. To measure health at the bank level I merge DealScan with Bankscope and the Federal Reserve's FR Y-9C tables. Details on DealScan and on sample selection are provided in Online Appendix B.

The matched Compustat-DealScan sample of R&D performers contains 522 medium- to large-sized firms. While the sample size is modest compared to work that relies on census data, the sample is economically large. Total sales of the firms equal 28% of U.S. GDP and they are responsible for 58% of U.S. corporate R&D in 2007. The latter implies that sampled firms conduct 21% more R&D than total business enterprise R&D in the entire EU.[10] The cyclical pattern of R&D in Compustat furthermore follows the pattern of aggregate spending closely (Barlevy 2007).

[7] This paper is also related to the literature on the effect of innovation and R&D on output and productivity growth. An elaborate discussion of past work and empirical strategies is provided in Cohen (2010).

[8] Firms that first appear in the data after 2003 are excluded to allow sufficient years to calculate a pre-crisis growth trend. Attrition in Compustat is high after 2015, for example through mergers and acquisitions.

[9] Because firm-bank links are required, firms without any syndicated loan from 1995-2007 are not sampled.

[10] This is based on the sum of all types of business enterprise R&D in 2007, OECD data.

2.2. Main Variables

The main variables of interest are intangible investments during the crisis and medium-term revenue growth. Intangible investments are measured through research and development (R&D). This captures the costs incurred for the development of new products and services, including software costs. They also include R&D activities undertaken by others for which the firm paid.[11] The intensity of investments during the Global Financial Crisis is found by taking the ratio of average annual investments in productivity in 2009 and 2010 to the stock of past R&D in 2007, approximated through the perpetual inventory method.[12] Investment in 2009 and 2010 are used because most firms reduced investments in those years compared to their peak in 2008.[13]

Medium-term output growth is measured through the growth rate of revenue, which is a standard outcome variable in the analysis of firm-level effects of innovative investments (e.g. Gabaix 2011, Bloom et al. 2013, Kogan et al. 2017, Bloom et al. 2017). I prefer this measure over productivity, on practical and theoretical grounds. Practically, revenue is directly observable from the income statement. Compustat lacks data on prices, which means that all measures of productivity capture revenue productivity. Revenue productivity is a measure of profitability, and (in the case of revenue TFP) furthermore requires an estimation of the production function. The dependent variable in the regression would therefore depend on the production function estimation method.[14] Theoretically, it depends on the model whether intangible investments should cause an increase in revenue productivity. Models of creative destruction, for example, predict no relationship between firm-level innovation and firm-level productivity. In the canonical Klette and Kortum (2004) model, innovative investments increase the number of products that firms have a production patent for. Successful innovation by firms allows them to produce a new or existing good at greater quality or productivity than the previous producer. If the good was previously produced at low productivity, the innovation allows it to be produced more efficiently and therefore raises aggregate TFP. At the firm level, however, the good may still be produced at lower productivity than the firm's other goods, therefore lowering the firm's average productivity.

Because the endogenous growth hypothesis suggests that a drop of intangible inputs slows the rate of technological progress, I do test the effect of exposure to the crisis on a firm's innovative output. The latter is measured through the value of patents that are awarded to firms between 2003 and 2015. I obtain patent data from Stoffman et al. (2019), who extend the dataset of Kogan

[11] This is particularly important as firms increasingly rely on external sources for R&D (e.g. Arora et al. 2016 and Chesbrough et al. 2006). The optimal measure of intangibles would also contain efforts to increase production efficiency like employee training. As data on such expenses is unavailable, the measures used here should be thought of as proxies for a firm's total effort to increase productivity.

[12] The stock then evolves along $a_{j,t+1} = a_{j,t}(1-\delta) + rd_{j,t}$. Past expenditures are assumed to depreciate along the literature's standard 15% depreciation rate for intangible capital investments (Li and Hall 2016). The initial stock equals investments over the depreciation rate. For robustness, all estimations have been conducted where the ratio of rd_j to the average of rd_j for three pre-crisis years was used to approximate investment intensity. This yields similar results.

[13] An alternative measure that is commonly used for R&D intensity is the ratio of R&D to revenue. The large demand shock during the crisis, however, means that variation in that measure is primarily driven by revenue rather than R&D.

[14] This problem is significant: for this paper's sample there is a *negative* correlation between firm-level TFPR estimated with the Wooldridge (2009) method and TFPR estimated with the De Loecker and Warzynski (2012) GMM method.

Table 1: Descriptive Statistics of Firm Characteristics

Variable	Median	Mean	St. Dev.	10th Pct.	90th Pct.	Obs.	Notes
Intangible Investment during Crisis							
Research and development	0.185	0.209	0.128	0.079	0.360	522	See text
Annual Revenue Growth							
Average 2003-2007	7.72	11.18	16.77	2.64	26.71	522	Percentage
Average 2008-2009	-11.79	-11.88	16.14	-32.94	7.43	522	Percentage
Average 2010-2014	3.23	2.98	8.98	8.52	14.34	522	Percentage
Characteristics, Avg. 2005-2007							
Sales	1145	6602	22131	76.94	12840	522	Mil. '09 USD
Employment	4.88	15.25	26.24	0.31	44.93	522	Thousands
Age (time since IPO)	3.37	3.43	0.51	2.77	4.16	522	Logarithm
Assets	1220	5666	11347	93.99	15593.12	522	Mil. '09 USD
Return on assets	5.09	3.86	7.90	-7.91	12.47	522	Percentage
Debt-to-assets	19.13	21.06	15.99	1.31	42.49	520	Percentage
Cash-to-assets	10.56	15.55	14.27	2.47	37.80	521	Percentage
Book-to-market ratio	-0.51	-0.53	0.66	-1.43	0.31	498	Logarithm
Price-earnings ratio	17.97	15.23	38.04	-26.42	47.68	501	Ratio

Descriptive statistics for the merged Compustat-DealScan sample. Includes all non-FIRE firms continuously present in the dataset from 2003 to 2014 that had positive R&D expenditures in at least one year between 2004 and 2007.

et al. (2017) until the end of my sample. The value of a patent is derived from a firm's excess stock returns within a narrow window around days in which firms are issued a patent. This serves as a quality-adjusted measure of innovative output at the firm level.[15] Section 4 elaborates.

2.3. Summary Statistics

Descriptive statistics for the firm variables are provided in Table 1. The upper panel summarizes the main variable of interest: investment intensity for R&D in 2009 and 2010, which equals 0.185 for the median firm. Annual real revenue growth is summarized in the middle panel. It was highest prior to 2008 when the median firm grew more than 7% per year. The bottom panel summarizes firm characteristics prior to the financial crisis, averaged for 2005 to 2007. The median firm employs almost 5000 employees, holds $1.2 billion in assets and sold over $1.3 billion prior to the crisis. This implies that sampled firms are much larger than average U.S. corporations. Return on assets, measured as the ratio of net income to real total assets, lies around 5%. Financial variables such as the book-to-market ratio are available for the sub-sample of firms on which data is available in CSRP. These firms have an average price-earnings ratio of 18% and a book-to-market ratio of 0.6. The distribution of firms across SIC sectors is summarized in Appendix Table A1.[16]

[15] This measure can only be calculated for publicly listed firms, which is a further advantage of the Compustat sample.

[16] The dataset contains a particularly large sample of manufacturing firms, as expected when conditioning on the performance of research and development. Within manufacturing, the sample contains a substantial number of firms in chemical, electrical, and computer products.

3. The Persistent Effect of Exposure to the Crisis

The first part of the analysis shows that the revenue of firms with greater exposure to the Global Financial Crisis is persistently lower in the aftermath of the crisis. Section 3.1 discusses the measures of firm-level exposure to the Global Financial Crisis, while section 3.2 presents the estimation equation and the estimated effect of exposure measures on medium-term revenue growth.

3.1. Measurement

To measure exposure to the Global Financial Crisis, I deploy two approaches. The first relies on the long-term nature of relationships between firms and banks. Firms tend to borrow from a limited number of financial institutions, as repeated interaction improves the ability of banks to screen and monitor lenders (Boot 2000). Firms that borrowed from banks *prior* to the crisis that were relatively restrictive in lending *during* the crisis therefore faced a stronger reduction in the supply of new loans. Consider an observable measure Ω_h^x that correlates with the reduction of credit supply by bank h during the Global Financial Crisis. To calculate the exposure of firm i through measure Ω_h^x, I calculate the weighted average of that measure across the set of banks that were involved in the last syndicated loan that firm i took out in the DealScan data prior to June 2007.[17] Chodorow-Reich (2014), on which this part of the analysis builds, shows that banks involved with the previous loan are most likely to participate in a firm's subsequent loan. The firm-level measure is:

$$\Omega_i^x = \sum_{h \in H} \theta_{ih} \cdot \Omega_h^x, \tag{1}$$

where θ_{ih} denotes the share of funds that bank h in syndicate H contributed to firm i's final loan.

I consider five measures for Ω_h based on previous work. The first four are used in Chodorow-Reich (2014). The first is the fraction of bank h's syndicated loans where Lehman Brothers acted as the lead lender, which captures the extent to which it was exposed to Lehman's failure.[18] The second measure quantifies a bank's exposure to the collapse of asset-backed securities (ABX), derived from the correlation between a firm's daily stock returns with an index that tracks the price of ABX securities issued in 2005 with, at the time, a AAA-rating.[19] The third measure is the ratio of deposits to assets in 2007. Banks with a relatively high stock of deposits have a stable source of short-term funding. Alternative sources of funding, like short term loans from other banks, were volatile due to the erosion of interbank markets during the crisis (e.g. Brunnermeier 2009). The fourth is losses in a bank's trading account as a fraction of assets in 2007-2008, as that is where most banks wrote

[17] If multiple loans were taken at the same date, shares are calculated over all loans. Because ψ is only available for a minority of loans in DealScan, it is imputed using the structure of syndicates. Shares of lead-arrangers and participants are based on average shares of either type in loans with the same number of leads and participants for which shares are available.

[18] Ivashina and Scharfstein (2010) explain this is because firms that borrowed from a syndicate with Lehman had to rely more on credit lines from other banks in the syndicate, preventing these banks from extending new loans.

[19] This is preferred over the use of balance-sheet derived measures of ABS-exposure, as foreign banks do not report such items consistently.

Table 2: Correlation Matrix of Firm-Bank Financial Crisis Exposure Measures

	Lehman Lead Share	ABX Exposure	Leverage Ratio	Deposits to Assets	Trading Gains
Firm-Bank Measures					
Lehman Lead Share	1.00*				
ABX Exposure	0.60*	1.00			
Leverage Ratio	0.33*	0.35*	1.00		
Deposits over Assets	0.42*	0.47*	0.11*	1.00	
Trading Gains over Assets	0.62*	0.52*	0.39*	0.65*	1.00

Each measure is calculated at the firm level along Equation (1).
Coefficients represent pairwise correlations, * indicates significance at the 5% level.

down subprime loans.[20] The final measure is the bank's financial leverage ratio in 2007, defined as its ratio of liabilities to equity. Banks with high leverage contracted credit more than other banks because losses of a given fraction of assets have a larger effect on equity. Correlations between the bank-health measures of exposure to the crisis are reported in Table 2.

Measures of exposure to the Global Financial Crisis from firm-bank links can be used to causally estimate the effect of a firm's exposure to tight credit if these measures (1) correlate with reductions in credit supply by banks (instrument relevance) and (2) are uncorrelated with unobserved determinants of medium-term revenue growth (instrument exogeneity). The first condition can be tested empirically by measuring the correlation between Ω_h^x and the change in lending by bank h during the crisis. In Table A2 of the Online Appendix, I show that these measures indeed predict a contraction of credit supply. Using a firm-level regression on the relationship between the crisis-change in new loans from banks that firm i borrows from to other firms, I find that a one-standard deviation increase in exposure reduces the number of new loans by 9 to 39 percent, depending on the measure. In Online Appendix Table A3 I show that exposed banks increased their credit spread, which shows that the decline in loans was not driven by a lack of demand for credit.

The second condition requires that banks are matched quasi-randomly to firms. While this cannot be verified with certainty, I do show that firms have similar observable characteristics and pre-trends in Section 4. This provides a first validation of instrument exogeneity if unobservable and observable confounders are correlated (e.g. Goldsmith-Pinkham et al. 2019, Oster 2019). I furthermore use the Khwaja and Mian (2008)-test to show that the predicted decline in loans from bank h to firm i does not depend on whether firm fixed effects are controlled for, which is a direct test of randomness in the assignment of banks to firms. Results and details of the analysis are provided in Tables A4 and A5 of the Online Appendix. Finally, my measures of crisis exposure Ω_h^x are not directly related to a bank's corporate lending operations, which further mitigates to risk of endogeneity even if firms were not randomly matched to banks.

As an alternative to measures of exposure to the crisis based on firm-bank links, I consider a firm-level measure that captures variation in debt structure. Specifically, it measures the percent-

[20] Chodorow-Reich (2014) furthermore uses real estate write-offs to measure exposure to the crisis, but this measure is not available in Bankscope.

age of a firm's long-term debt due the year after Lehman Brother's bankruptcy. Firms with a large fraction of their long-term debt due in middle of the crisis faced increased rollover risk and higher interest rates. This measure is valid if having a large percentage of long-term debt due does not reflect poor managerial practices, which may be an unobserved driver of long-term growth. Decisions on long-term debt payable right at the crisis' onset were made well before the crisis, however, which makes the measure plausibly exogenous. It was first used by Almeida et al. (2012), who show that firms with large portions of debt due were similar to other firms prior to the crisis on a number of dimensions, but reduced capital investments afterwards. This measure is only calculated for firms with positive long-term debt.

3.2. Estimation Equation and Results

I next show that exposure to the crisis has a persistent effect on revenue for each of these measures. To do so, I perform a panel regression where revenue is regressed on the (constant) measures of exposure to the crisis, interacted with year dummies to obtain their time-varying effect on revenue. The estimation equation reads:

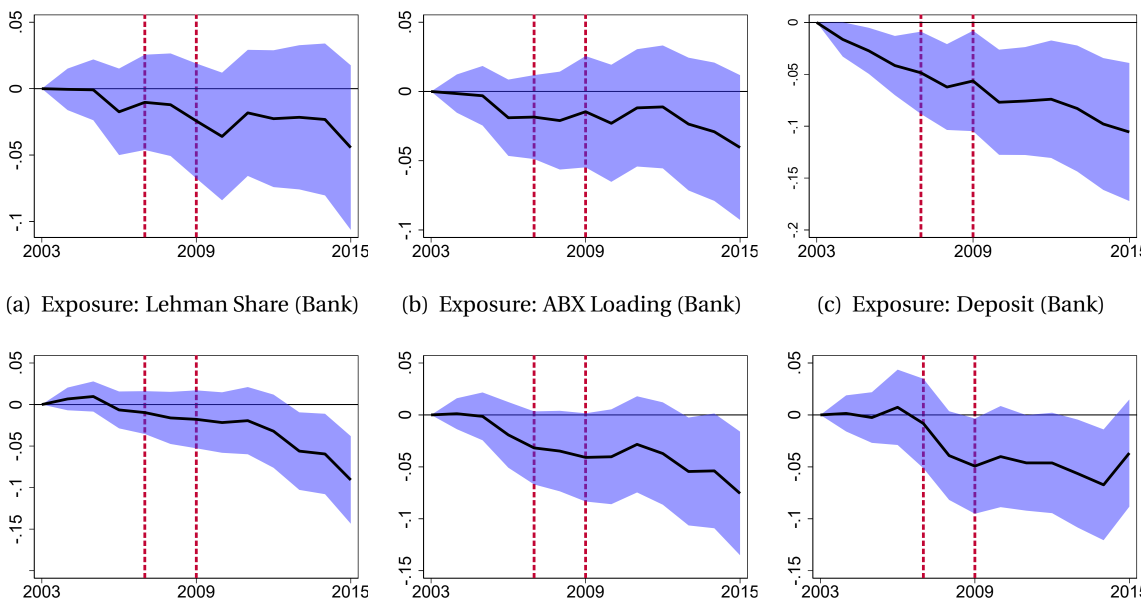
$$\log y_{ijt} = \phi_i^x + \psi_{jt}^x + \sum_{s \in T} \mathbb{I}_{t=s} \cdot \gamma_s^x \cdot \Omega_{ij}^x + \beta^{x\prime} z_{ijt} + \epsilon_{ijt}, \tag{2}$$

where y_{ijt} denotes revenue of firm i that operates in 2-digit industry j in year t. Firm fixed effects are denoted by ϕ_i^x, while sector-year fixed effects are denoted by ψ_{jt}^x. The six measures of exposure are denoted by Ω_i^x where $x = 1, 2, ..$; defined at the firm-level along Equation (1). $\mathbb{I}_{t=s}$ is an indicator function that equals one if an observation corresponds to year $h = 2004, 2005, ..$ etc. The first year of the sample (2003) serves as the baseline. z_{ijt} is a vector of control variables which include dummies for the calendar month in which the firm's fiscal year ends, which is usually December.

By estimating the relationship between revenue and crisis-exposure along equation (2) I absorb any unobservable drivers that are constant within the firm or that are common across firms within sectors within a year. While exposure to the crisis is a firm fixed effect, the interaction between exposure and years is not, such that γ_s^x can be estimated. Because the crisis should only affect revenue during and after the crisis, estimates of γ_s^x for 2004-2006 provide an additional test of the exogeneity of the crisis-exposure measures Ω_i^x.

Results are plotted in Figure 2. Each plot presents the path of γ_s^x over the time sample for a separate measure of exposure to the crisis. Figures (a) to (e) plot the response of revenue to exposure measures based on firm-bank links, while Figure (f) plots the response to having a large fraction of long-term debt due at the onset of the crisis. All measures are standardized to have unit standard deviations, standard errors are clustered by firm. Figure 2 shows that exposure to the crisis had a persistently negative effect on revenue. For a one-standard deviation increase in exposure, revenue is between 3 (share of debt due) and 10 (deposits) percent lower by the end of the sample. The path of revenue depends on the measure considered. For ABX exposure, leverage and trading

Figure 2. Effect of Crisis Exposure on Revenue



(a) Exposure: Lehman Share (Bank)

(b) Exposure: ABX Loading (Bank)

(c) Exposure: Deposit (Bank)

(d) Exposure: Leverage (Bank)

(e) Exposure: Trading Gains (Bank)

(f) Exposure: Debt Due (Firm)

Note: axis present estimated values of γ_s^x from Equation (2) and measure the percentage reduction in revenue from a one-standard deviation increase in exposure to the 2007-2008 financial crisis. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 (the start of the financial crisis) and 2009 (the final year of the crisis-induced recession). Coefficients in Figure (c) and (e) are multiplied by -1.

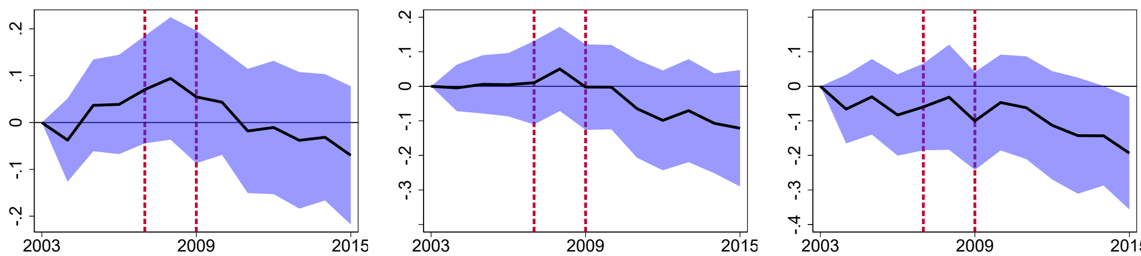
gains, there is little to no initial decline in revenue during the crisis. Over time, however, the effect of exposure to the crisis becomes increasingly large, reaching its peak at the end of the sample. Exposure to Lehman's failure and having a large share of debt due of the crisis has a more immediate effect on output, which persists over time. Figure (c), where exposure is measured through the ratio of deposits-to-assets at banks, is concerning: firms already face a shortfall in revenue from the start of the sample. This likely reflects unobserved heterogeneity across firms. Other measures do not show such pre-trends, however, and results in the remainder of this paper are robust to excluding a bank's deposits-to-assets as a measure of exposure to the 2007-2008 financial crisis.

I next analyze whether the decline in revenue of firms with greater exposure to the crisis is mirrored by a reduction in technological progress. I do so by measuring the effect of exposure on the value of patents that are awarded to firms. The estimation equation reads:

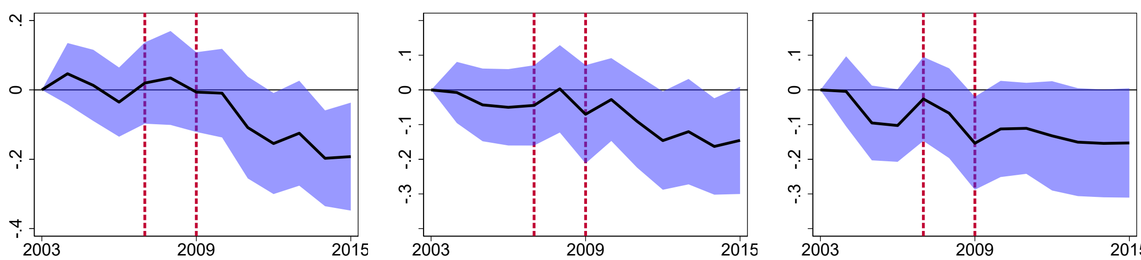
$$\log y_{ijt} = \phi_i^x + \psi_{jt}^x + \sum_{s \in T} \mathbb{1}_{t=s} \cdot \xi_s^x \cdot \Omega_{ij}^x + \beta^{x\prime} z_{ijt} + \epsilon_{ijt}, \tag{3}$$

where v_{ijt} is the value of patents awarded to firm i in section j during year t. The equation is otherwise analogous to Equation 2. The value of patents is measured in millions of dollars and is obtained from Stoffman et al. (2019). They extend the measure of Kogan et al. (2017), who derive

Figure 3. Effect of Crisis Exposure on the Value of New Patents



(a) Exposure: Lehman Share (Bank) (b) Exposure: ABX Loading (Bank) (c) Exposure: Deposit (Bank)



(d) Exposure: Leverage (Bank) (e) Exposure: Trading Gains (Bank) (f) Exposure: Debt Due (Firm)

Note: axis present estimated values of ξ_s^x from Equation (3) and measure the percentage reduction in patent value from a one-standard deviation increase in exposure to the 2007-2008 financial crisis. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 (the start of the crisis) and 2009 (the final year of the crisis-induced recession). Coefficients in Figure (c) and (e) are multiplied by -1.

the value of patents from the excess returns in stock prices for narrow windows around the dates on which firms are awarded patents. Their measure is available for all years of the sample, which makes it preferable over (e.g.) the Harvard Business School Patent Database, which ends in 2010.[21] The Kogan et al. measure is furthermore adjusted for the quality of a patent, as it is derived from the patent's effect on the firm's value. I define v_{ijt} as the sum of the value of all patents that are awarded to a firm in a calendar year and deflate the resulting amount with the GDP deflator.

Figure 3 presents the results. In line with the response of revenue, the value of patents awarded to firms with greater exposure to the Global Financial Crisis is persistently lower. All the measures of exposure that rely on firm-bank links show that the effect of exposures increases over time and continues until the the end of the sample. There are no pre-trends and no immediate effect of exposure on the value of awarded patents, which is expected as patents reflect the output of a firm's innovative investments. Firms with a greater share of their long-term debt due at the onset of the crisis do receive fewer patents as soon as in 2009, though the effect persists for the remainder of the sample too. The estimated effect is large: per standard deviation increase in exposure, annual patent awards fall by 10 to 20%, depending on the measure.

[21] Any immediate reduction in patenting behavior is unlikely to reflect a true reduction in technological progress at firms with high exposure to the crisis. This renders a dataset without post-2010 patent data unsuitable.

Table 3: Effect of Crisis Exposure on Intangible Investments

	(1) Lehman Lead Share	(2) ABX Exposure	(3) Deposits to Assets	(4) Leverage Ratio	(5) Trading Gains	(6) Share of Debt Due
Coefficient (univariate regression)	-0.008	-0.004	-0.016***	-0.015**	-0.001	-0.012**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Observations	522	522	522	522	522	458
R-squared	0.004	0.001	0.014	0.013	0.000	0.008
F-statistic	2.53	0.65	9.35	5.75	0.06	5.10

Note: Dependent variable is intensity of intangible investments in 2009-2010. Estimates obtained from univariate regressions on the measure in the column header. Estimates measure the effect of a 1 s.d. change in the variable. Industry-clustered standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1% level.

4. Intangible Investments and Growth

The previous section has established that firms with greater exposure to the Global Financial Crisis face persistent reductions in revenues and receive less patents. The endogenous growth narrative suggests that a lack of intangible investments during the crisis is the driver of that; this section analyzes whether that is the case. I first estimate the effect of exposure to the crisis on intangible investments in Section 4.1. I then use the fitted values of investments to explain the path of revenue and patent awards, controlling for changes to employment and capital investments during the crisis. Identification is discussed in Section 4.2, results are presented in Section 4.3.

4.1. Crisis-Exposure and Intangible Investments

I first estimate the correlation between exposure to the crisis and intangible investments in 2009 and 2010 as a fraction of the stock of past investments in 2007 using simple univariate regressions. As described in Section 2, investment in 2009 and 2010 are used because most firms reduced investments in those years, compared to the peak in 2008. Results are presented in Table 3. It shows that firms with greater exposure to the Global Financial Crisis invested less in intangible investments during the crisis. The correlation is significant for the leverage ratio, the deposits to assets ratio, and the share of long-term debt due.[22] Note that coefficients for deposits-to-assets and trading gains are multiplied by (-1). The coefficients are economically relevant: a one-standard deviation increase in exposure reduces investments around 1.5 percentage points for significant measures.

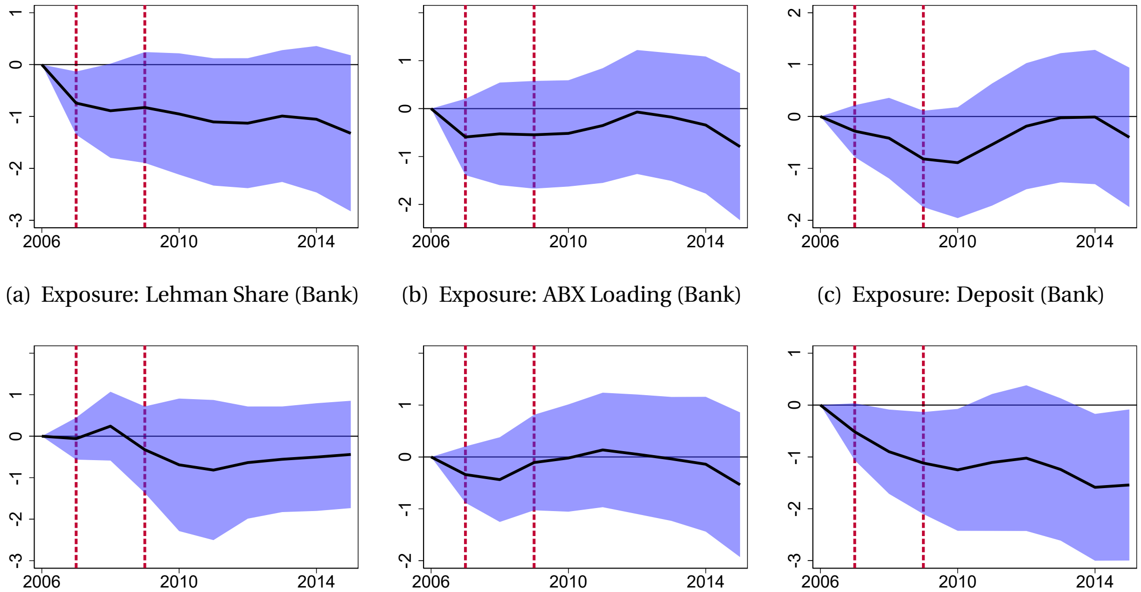
To perform the analysis dynamically I estimate an equation similar to (2):

$$Inv_{ijt} = \phi_i^x + \psi_{jt}^x + \sum_{s\in T} \mathbb{I}_{t=s} \cdot \chi_s^x \cdot \Omega_{ij}^x + \beta^{x\prime} z_{ijt} + \epsilon_{ijt}, \tag{4}$$

Analogous to the cross-sectional measure, investment is defined as the ratio of research and development in year *t* and *t+1* divided by the second lag stock. Control variables and measures of

[22] The p-value for significance of the Lehman Brothers' coefficient has a p-value of 0.12.

Figure 4. Effect of Exposure Measures on Intangible Investments



(a) Exposure: Lehman Share (Bank) (b) Exposure: ABX Loading (Bank) (c) Exposure: Deposit (Bank)

(d) Exposure: Leverage (Bank) (e) Exposure: Trading Gains (Bank) (f) Exposure: Debt Due (Firm)

Note: axis present estimated values of χ_s^x from Equation (4) and measure the percentage point reduction of intangible investments as a fraction of the intangible stock (see 1) from a one-standard deviation increase in exposure to the 2007-2008 financial crisis. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 (the start of the financial crisis) and 2009 (the final year of the crisis-induced recession). Coefficients in Figure (c) and (e) are multiplied by -1.

exposure to the crisis are defined analogous to Equation (2). Results are presented in Figure 4. Note that the investment variable is divided by the lagged stock, which precludes the inclusion of a long pre-trend in the figure.[23] The graphs show that, also when controlling for firm fixed effects and sector-year fixed effects, exposure to the crisis has a negative effect on intangible investments. The estimates in the figure are similar in magnitude to those in Table 3, though many coefficients are insignificant. This may be due to the inclusion of firm and sector-year fixed effect on a relatively small sample. It is also likely to reflect that the measure for intangible inputs captures only a fraction of the firm's innovative investments. Firms furthermore have discretion in what they refer to as research and development, making the measure noisy.

4.2. Intangible Investments and Growth: Strategy and Instrument Validity

In the final part of the analysis, I relate the persistent effect of exposure to the crisis to intangible investments during the crisis. In particular, I assess whether intangible investments in 2009-2010 (as analyzed above) explain revenue and patent awards for all other years in the sample. When

[23]This is possible, however, when looking at other measures of intangible investment spending. Section 4.2 shows that firms with greater crisis exposure do not show different trends in intangible investments between 2003 and 2007.

Table 4: Covariate Balance from Fitted Values of Intangible Investments During the Crisis

	Bank-Relationship Instruments				Incl. Share of Long-Term Debt Due			
	Low Exposure		High Exposure		Low Exposure		High Exposure	
Variable	N = 261		N = 261		N = 229		N = 229	
Investments, Avg. 2005-2007	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Research and development	0.198	0.073	0.180	0.069	0.194	0.073	0.183	0.070
Annual Sales Growth								
Average 2003-2007	0.123	0.151	0.101	0.181	0.110	0.135	0.114	0.200
Average 2008-2009	0.881	0.170	0.880	0.151	0.886	0.170	0.874	0.148
Characteristics, Avg. 2005-2007								
Age (log)	3.331	0.473	3.523	0.532	3.374	0.482	3.496	0.542
Assets (log)	6.588	1.535	7.685	1.977	6.619	1.589	7.800	1.953
Profitability	0.036	0.096	0.036	0.103	0.034	0.105	0.039	0.091
Leverage	0.186	0.156	0.236	0.161	0.186	0.157	0.242	0.159
Cash-to-Assets	0.175	0.156	0.135	0.125	0.177	0.161	0.126	0.109
Book-to-market ratio (log)	-0.566	0.663	-0.498	0.662	-0.578	0.652	-0.473	0.673
Price-earnings ratio	16.58	44.12	15.64	35.88	17.81	42.54	13.89	36.97
Fixed Effects	Spearman's Rank r		Product Mom. r		Spearman's Rank r		Product Mom. r	
Industry Code, 1-digit	0.93		0.99		0.81		0.98	
Industry Code, 2-digit	0.68		0.90		0.78		0.89	
Headquarter State	0.80		0.79		0.83		0.83	

Note: low and high exposure respectively refer to firms with fitted values of research and development above or below the median, from first stage regressions using bank characteristics, weighted by firm's last pre-crisis syndicate.

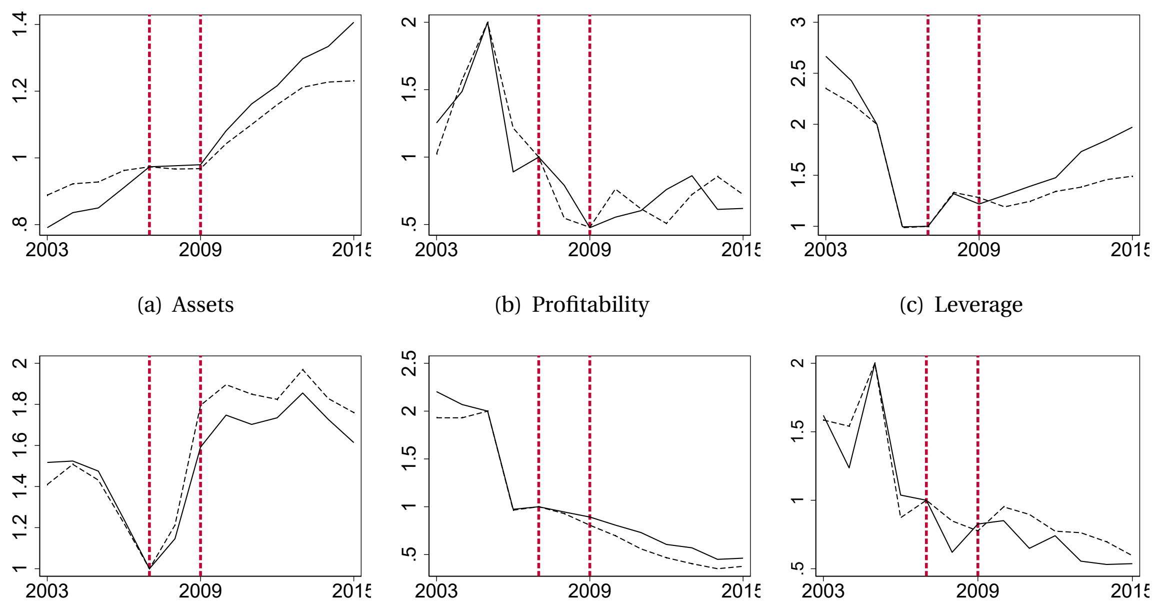
doing so, I instrument intangible investments in 2009-2010 with the measures of exposure to the crisis. This is done because the returns to such investments depend on the path of output that a firm predicts. A firm that expects its current set of products to face lower demand may invest in research and development to expand into new markets. Alternatively, a firm that expects demand for its goods to rise may invest in order to reduce its operating costs. Regardless of the direction, omitted variable bias prevents causal interpretation of OLS results.

For exposure measures to be valid instruments, they need to be relevant and exogenous. Results in Section 4.1 suggest that the instruments are relevant, though the lack of significance in Table 3 raises the concern that instruments are weak. To alleviate that, I estimate the first stage with multiple crisis exposure measures. I perform the analysis with two sets of instruments in the main text. The first includes all six measures of exposure to the crisis, including the crisis-exposure measure that is based on a firm's debt maturity, the second only uses the firm-bank measures.[24]

As in Section 3, measures of exposure must be orthogonal to the path of revenue that would have prevailed in absence of a crisis. Previous sections have shown that the instruments do not show pre-trends, and the Khwaja and Mian (2008)-test suggests that matching between banks and firms is close to random. Table 4 provides additional scrutiny by assessing whether pre-crisis variables are balanced across firms with high and low exposure. Firms are assigned high (low) exposure

[24] In the Online Appendix I reproduce the next section's results with different combinations of the exposure measures. Results are robust, for example, to excluding the deposits-to-assets ratio, which has a mild pre-trend in the reduced form analysis of exposure on revenue; and trading gains, which has the smallest coefficient in Table 3.

Figure 5. Covariate Trends from Fitted Values of Intangible Investments During the Crisis



(a) Assets (b) Profitability (c) Leverage

(d) Cash-to-Assets (e) Book-to-Market Ratio (f) Price-Earnings Ratio

Note: Solid (dashed) lines plot standardized means for firms with below (above) median exposure, respectively. Fitted values for intangible investments are from bank-relationship measures. Figure A4 in the Online Appendix uses the share of long-term debt due in 2009 as an additional measure of exposure, yielding similar results.

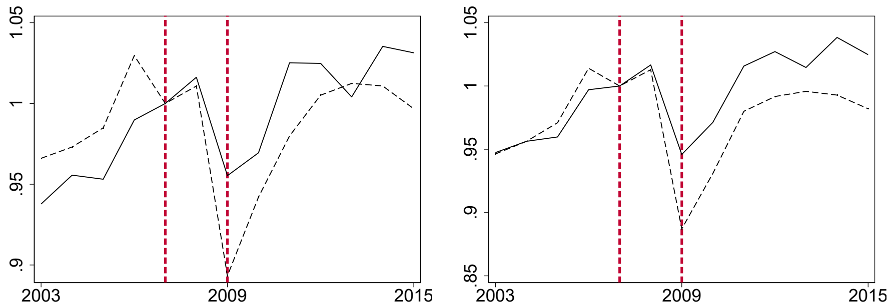
to the crisis if the fitted value of their intangible investments during the crisis (Inv_{ij}^{09-10}) is below (above) the median. The left panel uses exposure variables from firm-bank links to calculate the fitted value, the right panel uses all measures. Figure 5 additionally plots trend in the covariates using the firm-bank measures of exposure to the crisis; Figure A4 in the Online Appendix plots trends using all measures of exposure. Figure 6 plots trends of intangible investments.[25]

The table shows that average sales growth prior to the crisis and the decline in sales during the crisis is nearly identical for both groups. Values for fixed effects are also similar: the number of firms in each industry and state has correlation coefficients ranging from 0.79 to 0.99, while the rank correlation ranges from 0.68 to 0.93. Firms with high and low fitted values also have similar book-to-market and price-earnings ratios, suggesting that financial markets expected their future profitability and growth to be similar. There are some differences between both groups of firms: those with higher exposure to the crisis are larger, hold more cash and are slightly older. In the subsequent analysis, firm fixed effects absorb these pre-crisis characteristics.

To causally estimate the effect of intangible investments, the instruments would have to satisfy one additional requirement: they may not affect the path of revenue through other channels

[25] Plotting these variables provides additional insight into (the lack of) pre-trends over Figure 4. From regression results this is harder because of the inclusion of firm and sector-year fixed effects (Borusyak and Jaravel 2017). The Online Appendix provides similar figures for revenues, also over a much longer horizon.

Figure 6. Developments in Research and Development at Firms with High and Low Crisis Exposure



(a) R&D (exposure: bank) (b) R&D (exposure: all)

Note: Solid and dashed lines represent developments at firms with below and above median exposure, respectively. Fitted values in right-hand figures are from bank-relationship measures using R&D investments during the crisis as the dependent variable. The right figure uses the share of long-term debt due in 2009 as an additional measure of exposure, yielding similar results. Series are standardized to 1 in 2007.

than intangible investments. This condition is unlikely to hold: previous work (e.g. Almeida et al. 2012, Chodorow-Reich 2014) has convincingly shown that firms with greater exposure to the crisis reduce capital investments and employment, which may have persistent effects on output through adjustment costs or the loss of firm-specific human capital.

In the analysis I therefore explicitly control for capital investments and changes in employment during the crisis. By jointly estimating the effect of intangible investments, capital investments and changes to employment, I am able to analyze which of these three correlates most strongly with revenue over the medium run. Note that this reduces omitted variable bias from capital and employment, but does not address that research and development captures only a subset of a firm's innovative efforts. As long as such investments correlate more strongly with intangible investments then with changes to employment and capital, however, the estimated effect of intangible investments can be interpreted as the approximate effect of these type of investments as a whole.

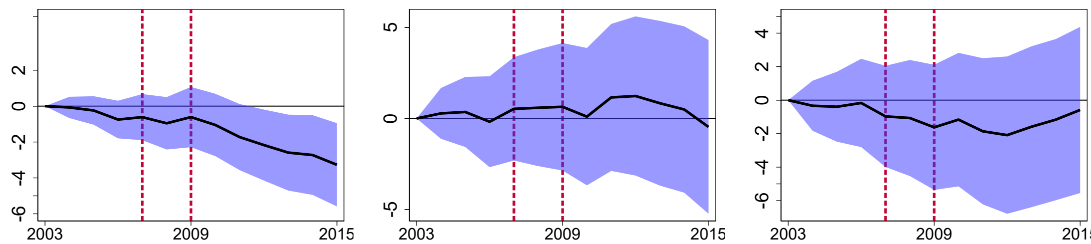
4.3. Intangible Investments and Growth: Results

I estimate the following equation in the second stage:

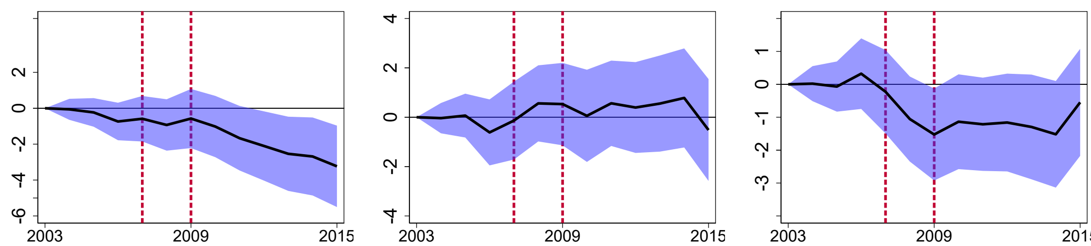
$$\log y_{ijt} = \phi_i + \psi_{jt} + \sum_{h\in T} \mathbb{1}_{t=h} \cdot \lambda_h^I \cdot \widehat{inv}_{ij} + \sum_{h\in T} \mathbb{1}_{t=h} \cdot \lambda_h^K \cdot \widehat{cap}_{ij} + \sum_{h\in T} \mathbb{1}_{t=h} \cdot \lambda_h^E \cdot \widehat{\Delta emp}_{ij} + \beta' X_{ijt} + \epsilon_{ijt} \quad (5)$$

where ϕ_i and ψ_{jt} respectively denote firm and sector-year fixed effects, $\widehat{inv}_{ij}$ denotes the fitted value of intangible investments in 2009 and 2010 divided by the stock in 2007, from the first stage regression on the crisis exposure Ω_i^x. $\widehat{cap}_{ij}$ is the counterpart for capital investment using property, plants and equipment in 2007 as the stock, while $\widehat{\Delta emp}_{ij}$ denotes the firm's change in employment in 2009-2010 as a percentage of employment in 2007. Because the first-stage regression relies on six (all measures) or five (firm-bank measures) instruments, I am also able to instrument

Figure 7. Effect of Intangible Investments, Capital Investments and Δ Employment on Revenue



(a) Intangible Inv. (bank Ω_i^x) (b) Capital Inv. (bank Ω_i^x) (c) Δ Employment (bank Ω_i^x)



(d) Intangible Inv. (all Ω_i^x) (e) Intangible Inv. (all Ω_i^x) (f) Δ Employment (all Ω_i^x)

Note: Vertical axis denote the percentage decline in revenue after a one-percentage point decrease in investments (Inv_{ij}^{09-10}) or employment. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 and 2009. Figures (a) to (c) instrument investments and employment with exposure measures based on firm-bank links, Figures (d) to (f) use all exposure measures.

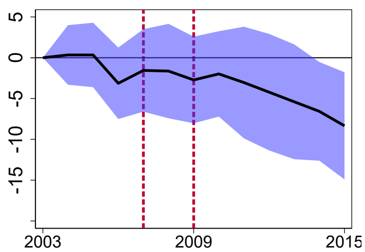
capital investments and changes to employment during the crisis. Provided that point estimates in the first stage differ, there is sufficient variation to estimate the year-by-year effect of the exposure measures jointly.[26] This is needed as, like intangible, they are endogenous to the path of revenue.

The main results are presented in Figure 7. The top three figures instrument intangible investments, capital investments and changes to employment with the five bank-health measures, while the bottom figures use the share of a firm's long-term debt due as an additional instrument. Both yield similar results: intangible investments have a persistently negative effect on revenue. The negative effect starts around 2011 and gradually increases over time. By the end of the time sample, revenue is around 3 percent lower for each percentage point decline in investment intensity. In contrast, capital investments and changes to employment during the crisis have a much smaller effect on revenue, and the effect wears off over time.

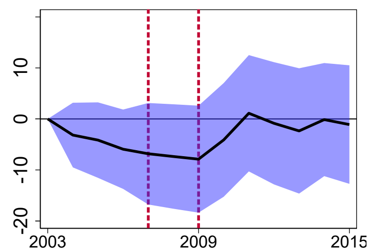
Figure 8 repeats the analysis with the value of patents as the dependent variable. This yields very similar results. Investments in intangible inputs during the crisis do not predict patenting behavior before and during the crisis, but cause a reduction in the value of patents awarded from

[26]For robustness, the Online Appendix shows that the estimated values of λ_h^I do not significantly change when capital investments and changes in employment are included as exogenous controls. This alleviates potential co-linearity concerns from using the same set of instruments for the three explanatory variables.

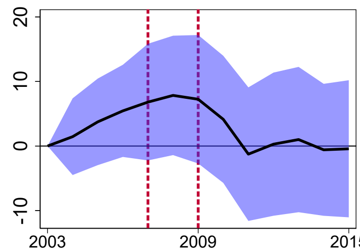
Figure 8. Effect of Intangible Investments, Capital Investments and Δ Employment on Patents



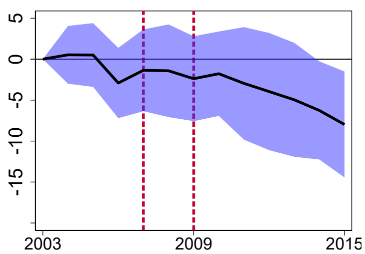
(a) Intangible Inv. (bank Ω_i^x)



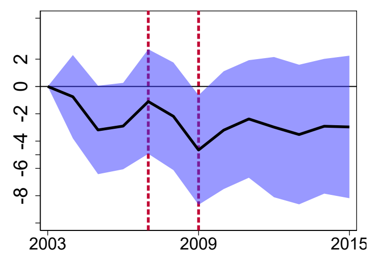
(b) Capital Inv. (bank Ω_i^x)



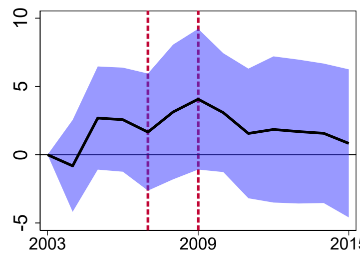
(c) Δ Employment (bank Ω_i^x)



(d) Intangible Inv. (all Ω_i^x)



(e) Intangible Inv. (all Ω_i^x)



(f) Δ Employment (all Ω_i^x)

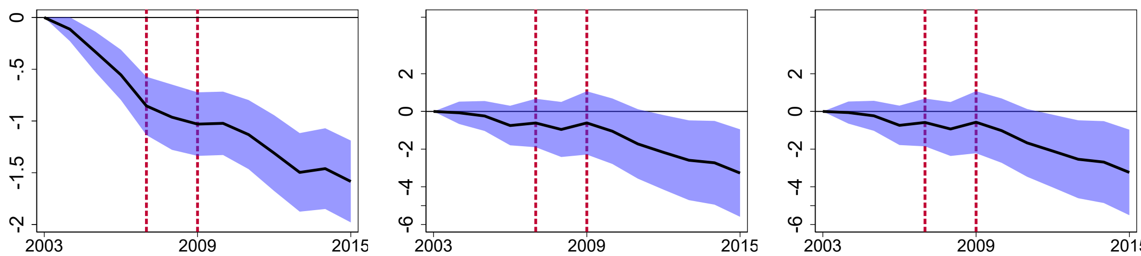
Note: Vertical axis denote the percentage decline in patent value after a one-percentage point decline in investments (Inv_{ij}^{09-10}) or employment. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 and 2009. Figures (a) to (c) instrument investments and employment with exposure measures based on firm-bank links, Figures (d) to (f) use all exposure measures.

2011 onwards. This is a strong indication that the crisis-induced reduction in intangible investments caused a decline of technological progress, in line with the endogenous growth hypothesis.

The results in Figure 7 and Figure 8 are robust to changes in the specification. Figure A1 of the Online Appendix presents the estimated effect of intangible investments on revenues and patents using the specification behind Figure 7(a) and (d) and 8(a) and (d) with alternative sets of instruments. Omitting the deposits-to-assets ratio, for example, does not significantly affect the estimates. Figures A2 and A3 show that adding capital investments and changes to employment during the crisis as exogenous rather than endogenous controls again yields similar results. Finally, the Online Appendix also contains tabled results on the effect of intangible investments on revenue growth after 2010. Rather than including firm fixed effects, they present a static analysis where pre-crisis firm characteristics such as its age, size (measured through assets), leverage, cash holdings, initial crisis exposure, lagged growth, book-to-market and price-earnings ratios are controlled for separately.[27]

[27] The additional controls are not available for all firms. This reduces the sample size the relevance of the first stage and causes insignificant estimates in a part of the second stage regressions (in particular those where the first stage F-statistics are low), though point estimates remain large. Note that all pre-crisis characteristics are absorbed in the results figures in the main text through firm fixed effects.

Figure 9. Effect of Intangibles on Revenue: Difference Between OLS and IV Results



(a) OLS Estimates (b) IV Estimates (bank Ω_i^x) (c) IV Estimates (all Ω_i^x)

Note: Vertical axis denote the percentage decline in revenue after a one-standard-deviation increase in the decline value of investments. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 and 2009. Figures (a) is from an OLS estimation of (5) that is otherwise unchanged.

To finalize this section, Figure 9 illustrates the importance of accounting for the endogeneity of (intangible) investments. The first figure plots the effect of investments during the crisis on revenue from an OLS estimation of (5), while the second and third figure are taken from Figure 7. While the long-term effect of intangible investments on output is smaller in the OLS estimation, there is a clear pre-trend: output of firms with lower investments during the crisis is already declining prior to 2007. This confirms the notion that investments are endogenous, for example because high-growth firms increase investments regardless of exposure to the crisis. Instrumenting these investments using exposure to the crisis resolves that problem and enables a more accurate assessment of the effect of intangible investments on post-crisis growth.

5. Conclusion

The aftermath of the Global Financial Crisis of 2007-2008 was characterized by a slow recovery, in which output did not recover to its pre-crisis trend. A growing theoretical literature suggests that endogenous growth can explain the slowdown: tight credit reduces intangible investments, temporarily slowing the rate of technological progress and leaving output on a lower trajectory.

This paper has analyzed the merits of that narrative. Using plausibly exogenous variation in firm-level exposure to the Global Financial Crisis, I first show that the crisis exerted a persistently negative effect on firm revenue and innovation, and that this effect grows over the medium-term. I further show that exposed firms reduce intangible investments during the crisis. Finally, I show that in a regression of intangible investments, capital investments and changes to employment, intangible investments are the only investments that predict the persistent decline in revenue and patent value of firms with high exposure to the Global Financial Crisis. Jointly, these results corroborate the endogenous growth hypothesis on the lack of recovery from the crisis.

The results are relevant for the debate on the post-crisis slowdown of productivity growth. Recent evidence suggests that the slowdown commenced prior to the crisis, and can therefore not be a consequence of the crisis. My results suggest that, while a secular slowdown in productivity growth may have commenced prior to the crisis, it was worsened by a lack of intangible investments during the crisis. The mechanism identified in this paper also implies that the effect of a one-time reduction in intangible investments on growth will wear off over time. Productivity should, therefore, regain some of its original growth rate over the coming years.

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Online Appendix

Appendix A. Additional Tables and Figures

Table A1: Distribution of Firms Across 2-digit SIC Industries

SIC 2-digit Code	Description	Count
01	Agricultural Production - Crops	1
10	Metal Mining	1
12	Coal Mining	1
13	Oil and Gas Extraction	6
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels	2
15	Construction - General Contractors & Operative Builders	1
16	Heamy Construction, Except Building Construction, Contractor	1
20	Food and Kindred Products	19
21	Tobacco Products	2
22	Textile Mill Products	4
23	Apparel, Finished Products from Fabrics & Similar Materials	1
24	Lumber and Wood Products, Except Furniture	3
25	Furniture and Fixtures	11
26	Paper and Allied Products	14
27	Printing, Publishing and Allied Industries	2
28	Chemicals and Allied Products	79
29	Petroleum Refining and Related Industries	3
30	Rubber and Miscellaneous Plastic Products	10
31	Leather and Leather Products	3
32	Stone, Clay, Glass, and Concrete Products	7
33	Primary Metal Industries	7
34	Fabricated Metal Products	20
35	Industrial and Commercial Machinery and Computer Equipment	73
36	Electronic & Other Electrical Equipment & Components	77
37	Transportation Equipment	41
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	50
39	Miscellaneous Manufacturing Industries	9
48	Communications	7
50	Wholesale Trade - Durable Goods	4
51	Wholesale Trade - Nondurable Goods	3
58	Eating and Drinking Places	3
73	Business Services	51
79	Amusement and Recreation Services	2
80	Health Services	1
87	Engineering, Accounting, Research, and Management Services	3

Table A2: Effect of Bank's Crisis Exposure and Δ New Loans to Other Firms[a]

	(1)	(2)	(3)	(4)	(5)
Exposure Variable:	Lehman Lead Share	ABX Exposure	Leverage Ratio	Deposits to Assets	Trading Gains
Effect on Δ New Loans	-0.330***	-0.480***	-0.094**	-0.253***	-0.389***
	(0.0729)	(0.0573)	(0.0402)	(0.0804)	(0.0847)
Observations	522	522	522	522	522
R-squared	0.271	0.571	0.022	0.159	0.375

[a]This table presents the results of univariate OLS regressions. The dependent variable is the ratio of new loans between October 2008 and June 2009 by banks $h \in H_i$ where H_i is the set of banks involved in firm *i*'s last pre-crisis syndicate) to other firms than *i*, divided by their new loans from October to June in 2005 and 2006 (multiplied by 0.5). The explanatory variable is the measure of crisis exposure (Ω_i^x in Equation 1) listed in the column header, standardized to have unit standard deviations. *, **, and *** respectively indicate significance at the 10, 5, and 1% level. Industry-clustered standard errors in parentheses.

Table A3: Effect of Bank's Crisis Exposure and Spreads[a]

	(1)	(2)	(3)	(4)	(5)
Exposure Variable:	Lehman Lead Share	ABX Exposure	Leverage Ratio	Deposits to Assets	Trading Gains
Effect on Spreads	0.048***	0.045***	0.047**	0.006	0.048***
	(0.008)	(0.009)	(0.021)	(0.015)	(0.008)
Observations	522	522	522	522	522
R-squared	0.271	0.571	0.022	0.159	0.375

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a]This table presents the results of univariate OLS regressions. The dependent variable is average spread in October 2008 and June 2009 by banks $h \in H_i$ where H_i is the set of banks involved in firm *i*'s last pre-crisis syndicate) to other firms than *i*, divided by the average spread from October to June in 2005 and 2006. The explanatory variable is the measure of crisis exposure (Ω_i^x in Equation 1) listed in the column header, standardized to have unit standard deviations. *, **, and *** respectively indicate significance at the 10, 5, and 1% level. Industry-clustered standard errors in parentheses.

Table A4: Khwaja-Mian Test: Randomness of Distribution of Banks over Firms (Part 1)[a]

	(1)	(2)
Δ Log lending in borrower-lender pair		
Δ New Loans	1.35***	1.40***
Borrower Fixed Effects	No	Yes
Observations	1,609	1,609
R-squared	0.01	0.39

[a]This table contains results for a test of randomness in the assignment of banks to firms in the spirit of Khwaja and Mian (2008). I implement the test in a similar fashion as Chodorow-Reich (2014), who also performs the analysis on DealScan (and, as expected, finds very similar results). The sample includes all *firms* that took out a loan during the crisis. The test involves running on a regression on the log-change in the volume of loans from bank $h \in H_i$, comparing loans during the crisis to loans in the final pre-crisis loan syndicate (which involved banks in the set H_i). The right hand side variable is the change in loans to other firms than i by firm $h \in H_i$, where the change is defined as in Table A2, which measures overall tightness of credit by bank h. Column (1) presents the univariate regression coefficient. Column (2) adds borrower fixed effects, which has a minimal change on the estimated coefficients. The positive coefficient means that firms took out more loans during the crisis from banks that were less restrictive in their overall credit supply if they had banks with different levels of crisis exposure in their last pre-crisis syndicate. The difference in the coefficients is a measure of the extent to which matching between firms and banks is not random as it captures unobserved borrower characteristics. The high degree of similarity in results of columns (1) and (2) suggest that this type of omitted variable bias is minimal. *** indicates significance at the 1% level, standard errors are clustered by lender.

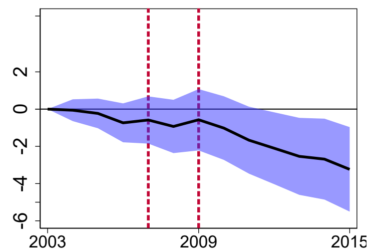
Table A5: Khwaja-Mian Test: Randomness of Distribution of Banks over Firms (Part 2).[a]

Exposure Variable:	(1) Lehman Lead Share	(2) ABX Exposure	(3) Leverage Ratio	(4) Deposits to Assets	(5) Trading Gains
Effect on Exposure Var. on Δ New Loans					
(1) Univariate	-0.218	-0.219***	-0.102**	-0.0805	-0.123
	(0.159)	(0.0744)	(0.0441)	(0.106)	(0.160)
Observations	1,628	1,170	1,412	1,493	1,257
R-squared	0.01	0.09	0.02	0.02	0.03
(2) Borrower Fixed Effects	-0.191	-0.206**	-0.105**	-0.0911	-0.128
	(0.151)	(0.0820)	(0.0495)	(0.0960)	(0.147)
Observations	1,628	1,170	1,412	1,493	1,257
R-squared	0.18	0.28	0.20	0.20	0.22

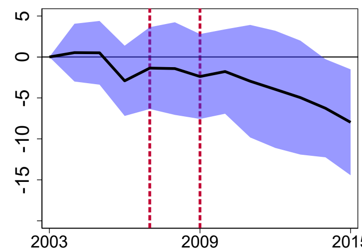
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a]In addition to the main test, conducted in Table A4, this table looks directly at the effect of including the crisis exposure measures Ω_h^x. It repeats the regressions of Table A2 at the lender-borrower level. Observation counts differ because not every member of each lending syndicate has data on all exposure measures. The regression shows that the relationship between credit tightness and measures of crisis exposure are not driven by unobserved characteristics of the lender. ***, **, and * indicates significance at the 10, 5, and 1% level, respectively. Standard errors are clustered by lender.

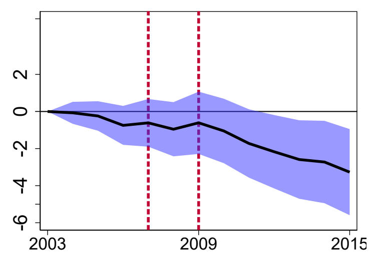
Figure A1. Effect of Intangible Investments: Alternative Instruments



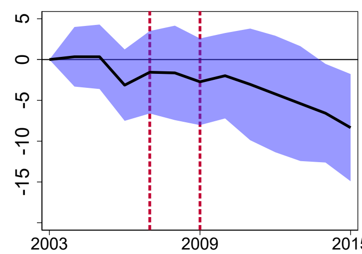
(a) Sales: All Instruments



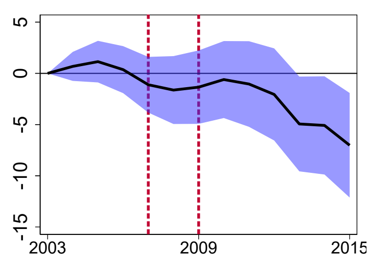
(b) Patents: All Instruments



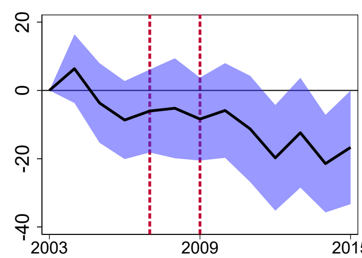
(c) Sales: All Bank Instruments



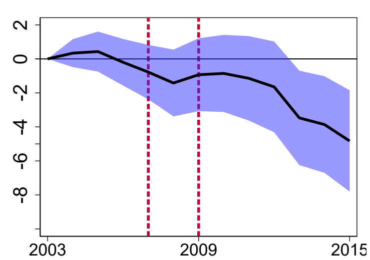
(d) Patents: All Bank Instruments



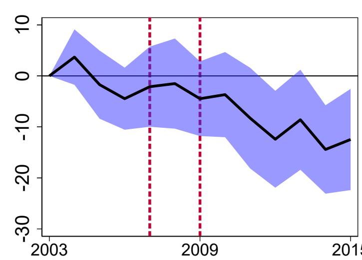
(e) Sales: Alternative IVs 1



(f) Patents: Alternative IVs 1



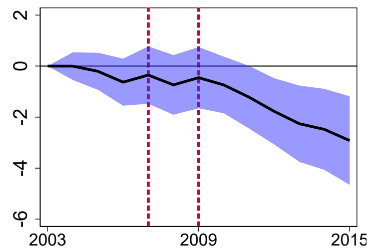
(g) Sales: Alternative IVs 2

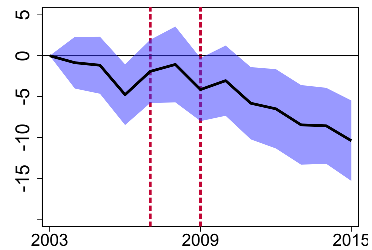


(h) Patents: Alternative IVs 2

Note: Vertical axis denote the percentage decline in revenue after a one-standard-deviation increase in the decline value of investments. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 and 2009. Figures (a) to (d) come from the main text. Figures (e) and (f) are from an estimation where the measure deposit-to-assets is not included as an instrument, and neither is the share of long-term debt due. Figures (g) and (h) additionally do not use trading gains as instruments, but do use the share of long-term debt due.

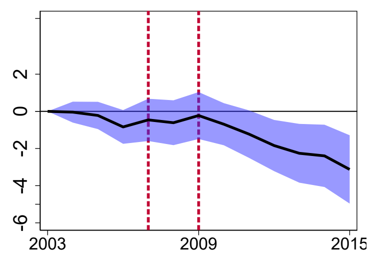
Figure A2. Effect of Intangible Investments: Capital and Labor Uninstrumented

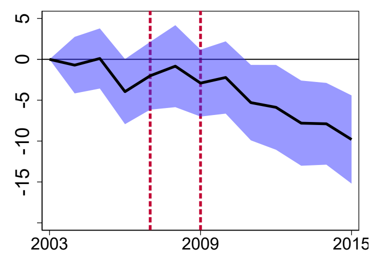




(a) Sales: Main Result

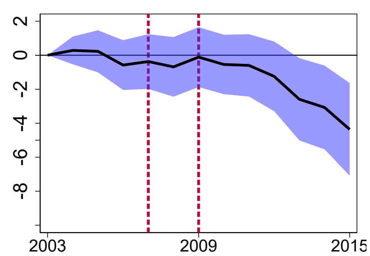
(b) Patents: Main Result

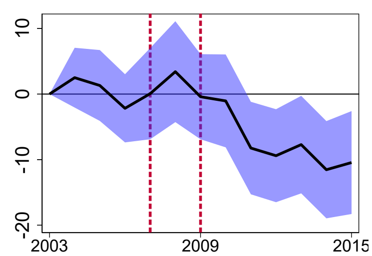




(c) Sales: Alternative IVs 1

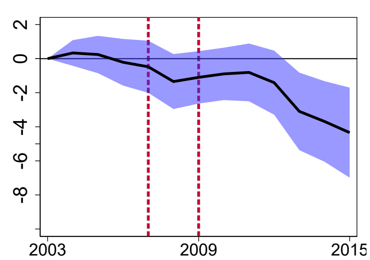
(d) Patents: Alternative IVs 1

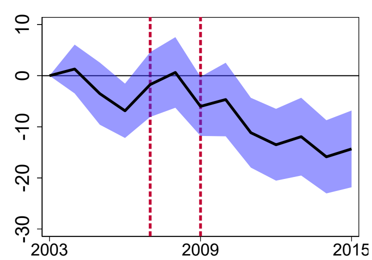




(e) Sales: Alternative IVs 1

(f) Patents: Alternative IVs 1



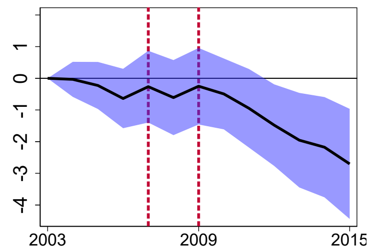


(g) Sales: Alternative IVs 2

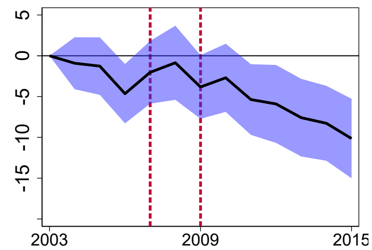
(h) Patents: Alternative IVs 2

Note: Vertical axis denote the percentage decline in revenue after a one-standard-deviation increase in the decline value of investments. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 and 2009. Figures (a) to (d) use the combination of instruments from the main text. Figures (e) and (f) are from an estimation where the measure deposit-to-assets is not included as an instrument, and neither is the share of long-term debt due. Figures (g) and (h) additionally do not use trading gains as instruments, but do use the share of long-term debt due. As opposed to the main text, this figure does not instrument capital investments and capital investments during the crisis, but considers them exogenous controls.

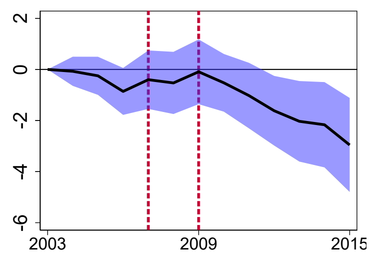
Figure A3. Effect of Intangible Investments: Capital and Labor Uninstrumented and Squared



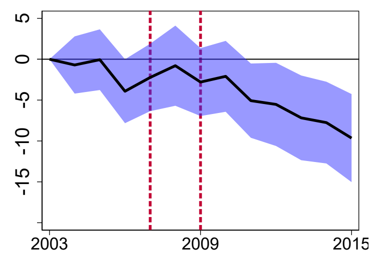
(a) Sales: Main Result



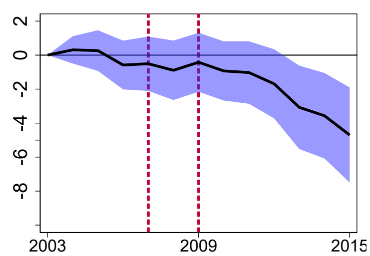
(b) Patents: Main Result



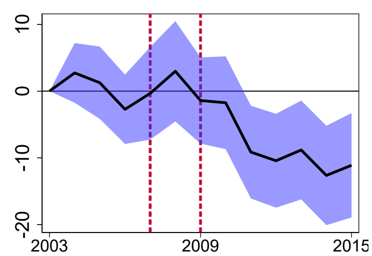
(c) Sales: Alternative IVs 1



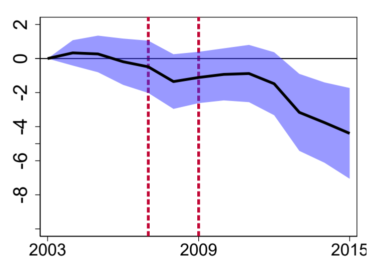
(d) Patents: Alternative IVs 1



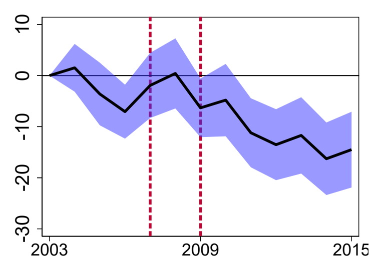
(e) Sales: Alternative IVs 2



(f) Patents: Alternative IVs 2



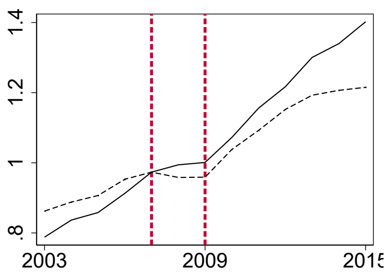
(g) Sales: Alternative IVs 2



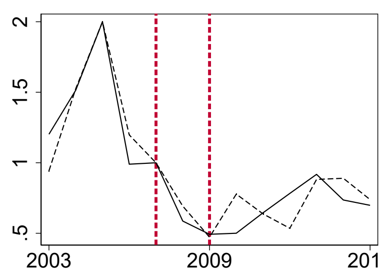
(h) Patents: Alternative IVs 2

Note: Vertical axis denote the percentage decline in revenue after a one-standard-deviation increase in the decline value of investments. Bounds present 90% confidence intervals based on firm-clustered standard errors. Vertical bars mark 2007 and 2009. Figures (a) to (d) use the combination of instruments from the main text. Figures (e) and (f) are from an estimation where the measure deposit-to-assets is not included as an instrument, and neither is the share of long-term debt due. Figures (g) and (h) additionally do not use trading gains as instruments, but do use the share of long-term debt due. As opposed to the main text, this figure does not instrument capital investments and capital investments during the crisis, but considers them exogenous controls. They are included both linearly and squared.

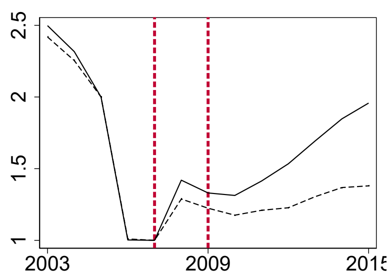
Figure A4. Developments in Covariates at Firms with High and Low Crisis Exposure



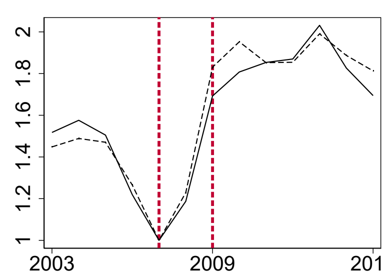
(a) Assets



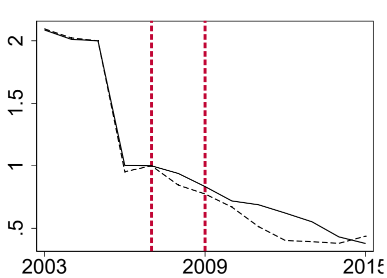
(b) Profitability



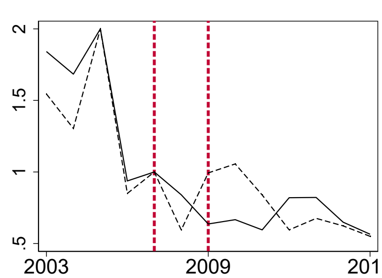
(c) Leverage



(d) Cash-to-Assets



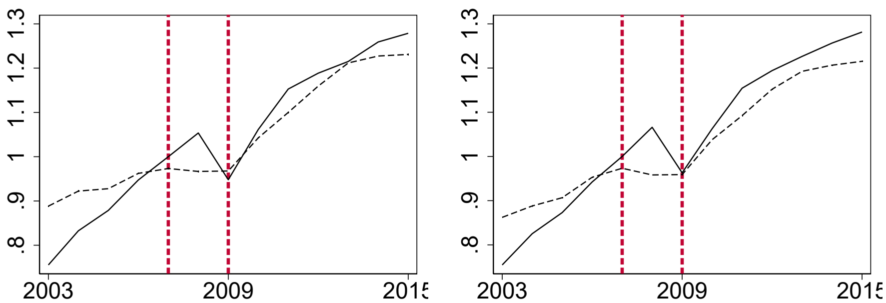
(e) Book-to-Market Ratio



(f) Price-Earnings Ratio

Note: Solid and dashed lines represent developments at firms with below and above median exposure, respectively. Fitted values are from bank-relationship measures using R&D investments during the crisis as the dependent variable, as well as the share of long-term debt due in 2009.

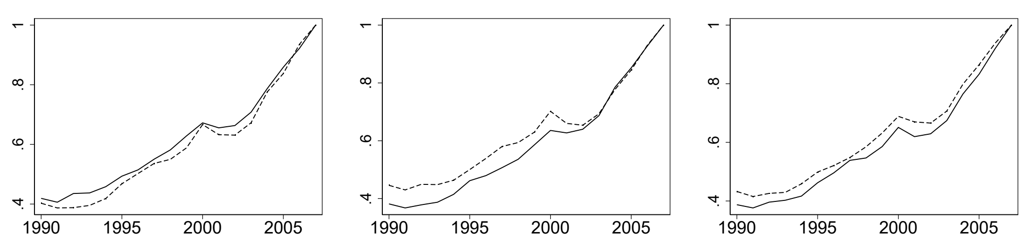
Figure A5. Developments in Revenues Variables at Firms with High and Low Crisis Exposure



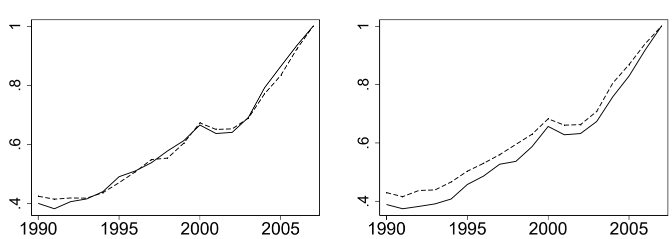
(a) Revenue (exposure: bank) (b) Revenue (exposure: all)

Note: Solid and dashed lines represent developments at firms with below and above median exposure, respectively. Fitted values in right-hand figures are from bank-relationship measures using R&D investments during the crisis as the dependent variable. The right figure uses the share of long-term debt due in 2009 as an additional measure of exposure, yielding similar results. Series are standardized to 1 in 2007.

Figure A6. Historical Pre-trends of Revenues of firms with High and Low Exposure from Bank Measures



(a) Exposure: Lehman Share (b) Exposure: ABX Loading (c) Exposure: Deposit-to-Assets



(d) Exposure: Leverage (e) Exposure: Trading Gains

Note: Average sales to firms with above-median (solid lines) and below-median (dashed lines) values for the exposure variables. 2007 = 1.

Table A6: Effect of Intangible Investments on Revenue (bank instruments)

Revenue Growth 2010-2014	(1)	(2)	(3)	(4)	(5)	(6)
R&D Investments	1.631*	1.746	1.674	2.114**	1.893*	2.351
	(0.871)	(1.078)	(1.163)	(1.014)	(0.974)	(2.016)
Capital Investment	-0.002	-0.006	-0.043	0.194	0.011	-0.615
	(0.030)	(0.039)	(0.031)	(0.329)	(0.155)	(0.646)
Δ Employment	-0.0371	-0.0308	-0.0441	-0.533	-0.171	0.538
	(0.0373)	(0.0427)	(0.0498)	(0.708)	(0.275)	(0.998)
Empl. and Cap. Instrumented	No	No	No	Yes	Yes	Yes
First-Stage Angrist-Pischke F						
Prod. Enhancing Inv.	8.583	12.22	10.04	7.694	13.78	7.998
Capital	-	-	-	1.340	7.521	0.638
Δ Employment	-	-	-	0.427	1.273	0.289
Control Variables						
Lagged Revenue Growth	Yes	Yes	Yes	Yes	Yes	Yes
Sector *Fixed Effects*	No	Yes	Yes	No	Yes	Yes
State *Fixed Effects*	No	Yes	Yes	No	Yes	Yes
Firm Characteristics	No	No	Yes	No	No	Yes
Stock Price Characteristics	No	No	Yes	No	No	Yes
Observations	507	507	487	507	507	487

Note: Dependent variable is Δy between 2010 and 2014. Instruments: deposits over assets, Lehman lead share, ABX exposure, leverage, trade gains. Bank variables are weighted by firm's last pre-crisis loan syndicate. Standard errors, clustered by industry, in parentheses. *, **, and *** denote significance at the 10 and 5, and 1% level, resp. Control variable definitions (avg. 2005-2007): Firm characteristics include pre-crisis assets (log), age (log), cash-to-asset ratio, profitability, leverage and loss of cash flow in '08. Stock price characteristics: book-to-market and price-earnings ratio.

Table A7: Effect of Intangible Investments on Revenue (all instruments)

Revenue Growth 2010-2014	(1)	(2)	(3)	(4)	(5)	(6)
R&D Investments	1.260	1.454	1.434	1.330	1.824*	2.224**
	(0.925)	(1.148)	(1.219)	(0.882)	(0.996)	(1.023)
Capital Investment	0.0179	0.0227	-0.00436	-0.0135	-0.104	-0.352*
	(0.0287)	(0.0369)	(0.0309)	(0.0967)	(0.0989)	(0.196)
Δ Employment	-0.0326	-0.0295	-0.0380	-0.0406	-0.0604	0.191
	(0.0446)	(0.0521)	(0.0501)	(0.162)	(0.133)	(0.233)
Empl. Change and Cap. Inv. Instrumented	No	No	No	Yes	Yes	Yes
First-Stage Angrist-Pischke F						
Prod. Enhancing Inv.	9.075	32.20	21.51	20.31	37.71	9.764
Capital	-	-	-	5.426	15.53	8.510
Δ Employment	-	-	-	4.970	4.398	3.375
Control Variables						
Lagged Revenue Growth	Yes	Yes	Yes	Yes	Yes	Yes
Sector *Fixed Effects*	No	Yes	Yes	No	Yes	Yes
State *Fixed Effects*	No	Yes	Yes	No	Yes	Yes
Firm Characteristics	No	No	Yes	No	No	Yes
Stock Price Characteristics	No	No	Yes	No	No	Yes
Observations	444	444	430	444	444	430

Note: Dependent variable is Δy between 2010 and 2014. Instruments: deposits over assets, Lehman lead share, leverage, ABX exposure, trade gains, share of debt due Bank variables are weighted by firm's last pre-crisis loan syndicate. Standard errors, clustered by industry, in parentheses. *, **, and *** denote significance at the 10 and 5, and 1% level, resp. Control variable definitions (avg. 2005-2007): Firm characteristics include pre-crisis assets (log), age (log), cash-to-asset ratio, profitability, leverage and loss of cash flow in '08. Stock price characteristics: book-to-market and price-earnings ratio.

Table A8: Effect of Intangible Investments on Revenue (alternative IV set 1)

Revenue Growth 2010-2014	(1)	(2)	(3)	(4)	(5)	(6)
R&D Investments	2.807*	2.804*	1.948	3.006**	2.902*	1.966
	(1.478)	(1.574)	(1.616)	(1.412)	(1.627)	(2.567)
Capital Investment	-0.011	-0.018	-0.045	0.068	-0.066	-0.758
	(0.0349)	(0.0449)	(0.0325)	(0.269)	(0.143)	(1.078)
Δ Employment	-0.092	-0.080	-0.056	-0.350	-0.052	0.772
	(0.062)	(0.0652)	(0.070)	(0.592)	(0.256)	(1.753)
Empl. Change and Cap. Inv. Instrumented	No	No	No	Yes	Yes	Yes
First-Stage Angrist-Pischke F						
Prod. Enhancing Inv.	4.297	6.964	3.260	7.864	10.72	5.306
Capital	-	-	-	1.975	4.708	0.433
Δ Employment	-	-	-	0.449	1.228	0.132
Control Variables						
Lagged Revenue Growth	Yes	Yes	Yes	Yes	Yes	Yes
Sector *Fixed Effects*	No	Yes	Yes	No	Yes	Yes
State *Fixed Effects*	No	Yes	Yes	No	Yes	Yes
Firm Characteristics	No	No	Yes	No	No	Yes
Stock Price Characteristics	No	No	Yes	No	No	Yes
Observations	507	507	487	507	507	487

Note: Dependent variable is Δy between 2010 and 2014. Instruments: ABX exposure, Lehman lead share, leverage, trade gains. Bank variables are weighted by firm's last pre-crisis loan syndicate. Standard errors, clustered by industry, in parentheses. *, **, and *** denote significance at the 10 and 5, and 1% level, resp. Control variable definitions (avg. 2005-2007): Firm characteristics include pre-crisis assets (log), age (log), cash-to-asset ratio, profitability, leverage and loss of cash flow in '08. Stock price characteristics: book-to-market and price-earnings ratio.

Table A9: Effect of Intangible Investments on Revenue (alternative IV set 2)

Revenue Growth 2010-2014	(1)	(2)	(3)	(4)	(5)	(6)
R&D Investments	3.566**	3.320**	2.750	3.727**	3.317**	2.569**
	(1.592)	(1.512)	(1.733)	(1.781)	(1.378)	(1.263)
Capital Investment	0.015	0.008	-0.008	0.044	-0.037	-0.295
	(0.0267)	(0.0367)	(0.0288)	(0.177)	(0.159)	(0.270)
Δ Employment	-0.143**	-0.117*	-0.0932	-0.249	-0.175	0.0904
	(0.0706)	(0.0666)	(0.0747)	(0.283)	(0.204)	(0.303)
Empl. and Cap. Instrumented	No	No	No	Yes	Yes	Yes
First-Stage Angrist-Pischke F						
Prod. Enhancing Inv.	4.283	7.779	3.109	4.411	11.02	5.849
Capital	-	-	-	6.198	8.263	3.250
Δ Employment	-	-	-	6.800	5.497	3.240
Control Variables						
Lagged Revenue Growth	Yes	Yes	Yes	Yes	Yes	Yes
Sector *Fixed Effects*	No	Yes	Yes	No	Yes	Yes
State *Fixed Effects*	No	Yes	Yes	No	Yes	Yes
Firm Characteristics	No	No	Yes	No	No	Yes
Stock Price Characteristics	No	No	Yes	No	No	Yes
Observations	444	444	430	444	444	430

Note: Dependent variable is Δy between 2010 and 2014. Instruments: ABX exposure, Lehman lead share, leverage, share of long-term debt due. Bank variables are weighted by firm's last pre-crisis loan syndicate. Standard errors, clustered by industry, in parentheses. *, **, and *** denote significance at the 10 and 5, and 1% level, resp. Control variable definitions (avg. 2005-2007): Firm characteristics include pre-crisis assets (log), age (log), cash-to-asset ratio, profitability, leverage and loss of cash flow in '08. Stock price characteristics: book-to-market and price-earnings ratio.

Appendix B. Data

This appendix contains a more detailed description on the creation of the dataset. The data comes from six underlying datasets. The main dataset is S&P's Compustat, from which I obtain variables for investments, revenue and covariates. Data on firm-bank relationships is taken from Thomson Reuter's DealScan. Exposure of banks to the Global Financial Crisis is obtained from both Dealscan, Bureau van Dijk's Bankscope, and the Federal Reserve's FR Y-9C tables. Stock price data is obtained from CRSP, patent data is obtained from Stoffman et al. (2019) and Kogan et al. (2017).

Compustat I start from the Compustat Annual file and keep firms that report R&D at least once the three years prior to the crisis. I drop observations with missing or negative total assets and sales, as well as firms that enter the dataset after 2003 or exit before 2015. Firms in finance, insurance and real estate, as well as firms in regulated utility sectors are excluded. Stock price and market capitalization data is obtained by merging the resulting dataset with CSRP. All variables are deflated using the BEA's GDP deflator and are winsorized for the bottom and top 15 firms.

DealScan DealScan obtains loan-level data from SEC filings, complemented by sources such as news reports and contacts inside borrowing and lending institutions. Because DealScan takes data on loans from public sources, the majority of loans (73%) in DealScan is syndicated. In contrast to standard loans, syndicated loans are provided by a group (the syndicate) rather than an individual lender. The choice to divide loans amongst participants is usually driven by the desire to diversify on the side of banks, as syndicated loans can be very large. They take the form of fixed term loans, bridge loans, credit lines, leases, or most other conventional forms. Firms seeking a syndicated loan arrange the basic terms with a lead arranger, also known as the underwriting bank. Once the loan amount, interest rate and conditions like collateral and fees have been agreed upon, the lead arranger recruits other investors to participate in the loan. Loans in DealScan account for over 75% of commercial loans in the U.S., making it the most complete overview of debt transactions available and the primary source of bank loan data for research.[28]

To select the sample of loans from DealScan, I roughly follow the criteria in Sufi (2007), Ivashina and Scharfstein (2010) and Chodorow-Reich (2014). Loans with start dates prior to 1995 are not included as DealScan's coverage increased substantially from that year onwards. Loans with extraordinary purposes, such as management buyouts, are also excluded.[29] Following Chodorow-Reich (2014), I also require that at least one of the lenders for each loan is part of the top 43 of overall lenders and drop lenders without any loans two years prior to the crisis, to allow balanced matching with bank data later on. Finally, 260 loans with values below $10,000 are excluded.

Bank Data Data on the health of banks is obtained by merging the Compustat-DealScan dataset of R&D performers with bank balance sheet variables using Bureau Van Dijk's Bankscope and Federal Reserve FR Y-9C tables. Bankscope is used for data on international banks and investment banks, while Y-9C data is used for American depository institutions. The datasets are merged using a script kindly provided by Gabriel Chodorow-Reich. His file creates links for 258 banks which are responsible for the creation of 85% of loans in the year prior to the crisis. Amongst the remainder, I hand-match 90 large lenders to Bankscope and Federal Reserve identifiers. Combined, matched banks are responsible for issuing over 93% of DealScan loans. For Y-9C data, deposits are calculated as the sum of total demand deposits (item 2210), total non-transaction saving deposits (item 2389) and total time deposits (the sum of items 2604 and 6648). For Bankscope data, the sum of consumer and bank deposits (items 2031 and 2185) is used.

[28] Carey and Hrycray (1999) find that between 50 to 75% of the volume of commercial loans is included in the dataset, and a large majority of large loans. Coverage since the 1990s is even better (Chava and Roberts 2008).

[29] Specifically, loans for general corporate purchases, asset acquisitions, aircraft finance, credit enhancement, debt refinancing, project, hardware and software financing, equipment purchases, real estate financing, ship finance, telecoms build outs, trade finance and working capital are included.