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Abstract

We find a negative relationship between bank distress and the level, quality and trajectory of firm-level innovation during Great Depression, particularly for R&D firms operating in capital intensive industries. However, we also show that because a sufficient number of R&D intensive firms were located in counties with lower levels of bank distress, or were operating in less capital intensive industries, the negative effects were mitigated in aggregate. Although Depression era bank distress was associated with the stifling of innovation, our results also help to explain why technological development was still robust following one of the largest shocks in the history of the U.S. banking system.

JEL: N22, G21, O30
Keywords: Great Depression, Patents, R&D, Bank Distress

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I Introduction

There is increasing evidence linking the health of the financial sector to outcomes in the real economy (King and Levine, 1993; Jayaratne and Strahan 1996; Rajan and Zingales, 1998; Black and Strahan, 2002). Studies of the recent financial crisis have shown that when bank lending dries up, shocks to the availability of credit can constrain resource allocation and severely depress firm-level investment (e.g., Kashyap et al., 1994; Paravisini, 2008; Campello et al., 2010; Ivashina and Scharfstein, 2010; Lemmon and Roberts, 2010). Fewer studies, however, have examined the link between the health of the financial sector and technological development, which is an important gap in our understanding given that innovation acts as a main driver of the real economy through its impact on aggregate output and productivity growth.[1]

The Great Depression provides a useful context for such a study.[2] Richardson (2007, 2008) finds that 5,189 banks failed from January 1st 1929 through February 28th 1933, which would have had a strong impact on access to capital through the bank lending channel (e.g., Friedman and Schwartz, 1963; Temin, 1976; Bernanke, 1983; White, 1984; Wicker, 1996; Calomiris and Mason, 1997, 2003; Grossman, 2010; Graham, Hazarika and Narasimhan, 2011; Carlson and Rose, 2011). Yet, despite this level of bank distress, aggregate productivity statistics show that the 1930s was the most innovative decade of the twentieth century (Field, 2003, 2011). Although productivity dropped from 1929 to 1933 and output fell precipitously (between the peak in August 1929, and the trough of May 1933 real GDP fell by 39 percent), industries like chemicals, television and radio experienced fundamental phases of innovation (Bernstein, 1989; Szostak, 1995). During the 1930s the automobile sector experienced one of the most important technical breakthrough periods in its history (Raff and Trajtenberg, 1997).

If the health of the financial sector is so critical to the functioning of the real economy, how can it be reconciled that technological development continued to advance rapidly

[1] Brown, Fazzari and Petersen (2009) analyze the effects of finance on R&D during the 1990s, Atanassov, Nanda and Seru (2007) examine the nature of bank vs. equity finance and the nature of firm innovation, and Hall and Lerner (2010) survey the literature more generally

[2] Analogously, in their study of corporate governance and corporate performance, Graham, Hazarika and Narasimhan (2011) argue that the Depression "can be viewed as an exogenous event at the firm level and hence provides an ideal setting to test our predictions in a 'before-and-after' comparison."

despite a disrupted financial system? Although prior work on this period has extensively examined the causes of the financial crises, little work has been done on identifying the impact of bank distress on innovation at the firm-level. Bernanke (1983) implies the effect should be large given that bank failures destroyed information capital, leading to higher financial intermediation costs in establishing contracts between lenders and borrowers. More recently, Richardson and Troost (2009) find a strong link between bank credit contraction and declines in wholesale trade and Mladjan (2011) connects bank distress with falls in output, especially in sectors such as rubber that depended heavily on access to capital. On the other hand, using a general equilibrium framework, Cole and Ohanian (2000, 2004) assert that "banking shocks account for a small fraction of the Great Depression." Their preferred explanation for the duration of the 1930s downturn is the negative impact of New Deal cartelization and labor law policies.

We use novel micro-data on corporate R&D to examine the link between financial sector distress and technological development. Two features of the data allow us to move beyond the aggregate analysis of productivity growth in the 1930s to study whether, and if so how, firm-level innovation was impacted by the banking crises. First, we are able to create a firm-level panel of corporate innovation, by matching patent and patent citation records from the U.S. patent office to individual firms included in the National Research Council's (NRC) direct correspondence surveys of industrial research labs. These surveys have comprehensive coverage of the corporate R&D sector, spanning R&D labs by large public firms such as DuPont and General Electric, but also including small, private firms that were involved in innovation (Mowery and Rosenberg, 1998; Nicholas, 2011). Our data thus provides us with close to the universe of corporate R&D patenting over the period we study. Although the NRC surveys were not undertaken each year, firms included in these surveys can be matched to patent records to create an annual panel of innovation. Importantly, the panel spans the period 1920 to 1938, so we can examine innovation before, during and after the banking crises.

Second, we use information on the physical address of each firm in our dataset to establish the county in which they were located and we link these data to county-level data on banking in the United States from 1920 to 1936, as compiled by the FDIC. This

dataset contains information on end-of-year deposits in all banks, the number of active banks and the number of suspensions for all banks, national banks and state banks for all counties, other than those in Wyoming.[3]

We exploit cross-county variation in the severity of bank distress faced by the firms in order to understand the extent to which bank distress in a firm's local banking market impacted the level and trajectory of corporate innovation. Restrictions on the banking sector at the time meant that banks could not branch across state lines and were often made up of unit banks. Only in California was there any extensive branching outside the bank's home office city (Carlson and Mitchener, 2009). Hence, a significant portion of firm borrowing came from local banks, even for large, publicly-traded corporations.

Our empirical strategy has three parts. First, we use difference-in-differences specifications to examine the quantity, quality and novelty of patenting by private firms relative to publicly traded corporations in the periods before and after the bank failures. Consistent with the view that rising costs of financial intermediation especially harm smaller enterprises (Bernanke, 1983; Kerr and Nanda, 2009), we find that private firms in our post period experienced declines in R&D output relative to publicly traded firms. Patents fell by 27 percent relative to publicly traded firms, citations by 45 percent and average citations per patent by 23 percent. We also show that firms shifted the trajectory of innovation to more incremental activities. We use two measures of patent novelty - *originality* and *generality* - which identify patents starting a citation trail and patents affecting a broad set of subsequent patent classes respectively. We also find a negative impact in our post-period on these measures. To the extent that patents with high *originality* and *generality* scores are characteristic of radical inventions, this suggests that bank distress was associated with a shift away from high-risk R&D projects for private firms relative to publicly traded firms.

Although Friedman and Schwatrz (1963) argued that bank failures were driven primarily by panics, an important concern with the estimates in the first part of our analysis is that they may be confounded by demand shocks which caused private firms to patent

[3]As noted by Calomiris and Mason (2003, p.1643), Wyoming is excluded from the FDIC data. Under the dual banking system, state banks fell under the regulatory system of state banking departments while national banks were regulated by the Office of the Comptroller of Currency.

less and banks to suspend more. The second part of our analysis therefore focuses only on publicly traded firms. We exploit the fact that public firms that sold into a national market would have been subjected to similar aggregate demand shocks while restrictions on bank branching at the time implied that they still relied on local banks for some of their financing needs. This allows us to control for aggregate demand fluctuations using industry and year fixed effects, while still comparing firms that were based in more versus less stressed counties. Furthermore, we examine whether the difference in innovation across more versus less stressed counties was driven by firms operating in sectors with different capital requirements. When running our regressions on firms that were more or less dependent on external finance, we show that the negative effect of bank distress on innovation is dominated by the heavily dependent firms and additionally that the effect of bank distress on R&D output is statistically insignificant for firms operating in less capital intensive industries. The differential effects we find by capital requirements helps to explain why bank distress would have stifled innovation for only a subset of R&D firms during the 1930s. Indeed, we find the aggregate effect of bank stress on innovation by publicly traded firms to be weak.

Third, we present robustness checks on the results from the second part of our analysis and attempt to isolate mechanisms. We draw on the literature documenting a strong relationship between a community's social structure and its susceptibility to bank panics to construct an instrument for bank distress. Specifically, we measure the cohesiveness or fragmentation of the social structure of each county using data from the 1906 Census of Religious Bodies to separate out the supply side effect of bank distress from aggregate demand shocks. Our results support the hypothesis that bank distress negatively affected innovation. Next we use county-by-year fixed effects to show that time-varying differences across more versus less distressed counties do not confound our results. Finally, we use data on firm-level R&D employment and the number of laboratories operated to show that our results are not being driven by bank distress only indirectly leading to a reduction in innovation through its effect on input usage.

Overall, our findings indicate that bank distress during the Great Depression was associated with a large reduction in the level and quality of innovation by the firms that

were most affected. Our patent novelty measures also suggest that firms in distressed counties were considerably more conservative in the innovation they pursued and the types of R&D projects that were undertaken. Crucially, however, we also show that the localized nature of the bank failures meant that a sufficient fraction of the most active patenting firms were located in counties with relatively low bank suspension rates, or were operating in industries that were less dependent on external finance. Our dynamic specifications show that even the worse hit firms were beginning to catch up with their less hit counterparts in terms of innovation by the end of the 1930s. In aggregate, therefore, we are able to reconcile two previously contradictory views of the Great Depression: one where the banking crisis should have impacted real activity such as firm-level innovation and another where important advancements took place in innovation across a number of industrial sectors at a time of unprecedented distress to the U.S. financial system.

The remainder of the paper is organized as follows. The next section provides a historical background to banking, finance and technological development during the Great Depression in order to outline our strategy for identifying the effect of banking sector distress on innovation. Section three describes the NRC R&D firm data, patent and citations data and FDIC bank data. Section four presents the empirical framework and results. Section five reports the results from our robustness checks and Section six discusses our findings and concludes in light of aggregate evidence on innovation during the 1930s.

II Bank Distress and Financing Innovation

In the literature on the financing of innovation it is well-established that the propensity of firms to undertake R&D depends on their ability to satisfy current capital expenditures and to borrow in the future to meet potentially large adjustment costs (e.g., Levine, 2005; Hall and Lerner, 2010). Although not all firms would have borrowed to directly finance their innovation activities in the 1930s, R&D would have been impacted by disruption to the banking sector that prevented firms from smoothing out expenditures in the face of a large liquidity shock. Even firms that were not directly financing their innovation through bank debt would have been impacted, as internal cash flows were diverted to fund more "essential" activities by firms unable to access sufficient external finance. This

was particularly true of the early twentieth century, when the widespread use of capital markets was uncommon (Mitchener and Wheeler, 2010) and many firms relied on renewable short-term funds provided by banks, even to finance longer-term investment (Jacoby and Saulnier, 1947).[4]

Bernanke (2000, pp.63-64) points to a large body of contemporary evidence showing that firms faced severe difficulties accessing working capital and finance for long-term investments in the 1930s, even for elite firms with a track record of commercial credit. Calomiris and Mason (2003, p.937) summarize the fundamental effect that banking sector distress in the 1930s had on firm-level investment:

> Many firms and individuals relied on banks for credit, and as those banks suffered losses of capital (due to asset value declines) and contractions in deposits (as depositors reacted to bank weakness by withdrawing their funds), even borrowers with viable projects and strong balance sheets experienced a decrease in the effective supply of loanable funds.

Although publicly traded firms relied on the equity markets to finance investment during the 1920s, this conduit was severely disrupted following the stock market crash in 1929 (Reinhart and Rogoff, 2009). Using data from *Moody's Investor Service* Figure 1 illustrates the sharp fall in public equity and debt financing in the early 1930s, which meant that firms would have been unable to fully substitute bank financing with capital from public markets. Thus, bank distress would have impacted the ability of publicly traded firms to access external finance.

II.A Local Financing by Banks

Related literature also suggests that local bank financing mattered a great deal for the financing activities of firms. Constraints on interstate branch-banking implied that local banking conditions had a clear effect on local lending. For example, Calomiris and Mason (2003) report that during the Depression years, a fall in the growth rate of bank loans

[4]Consistent with the fact that even large publicly traded firms relied to bank financing, bank credit is a much smaller share of overall credit in the economy today than it was during the Great Depression. Historical Flow of Funds data from the Federal Reserve Board provide data from the mid 1940s onwards. Bank loans accounted for about 25 percent of credit provided to non financial corporate businesses between 1946 and 1955. In contrast, bank lending accounted for 9 percent of credit to the same class of businesses between 2005 and 2012 (10 percent looking only from 2005-2006).

was associated with a substantial drop in local income growth. In a further contribution, Ziebarth (2011) finds economically important effects of bank distress on manufacturing activity in Mississippi. He compares establishments in districts of the state that fell under the Atlanta Federal Reserve, which provided liquidity to mitigate bank distress, with districts under the St. Louis Federal Reserve, which did not expand credit supply counter-cyclically. Ziebarth estimates that this difference in policy approaches explains around 60 percent of the fall in industrial production from 1929 to 1931.

A prominent example of local financing affecting firm-level outcomes in our data is the automobile industry in Detroit, which was heavily research intensive (Raff and Trajtenberg, 1997). By 1927, 56 percent of Detroit's economy was based on car manufacturers and component suppliers (Curcio, 2001, p.505). When banking panics caused firms to suspend their activities during the early 1930s, the Ford Motor Company provided approximately $12 million in loans to local banks to avert the crisis. Ford lost heavily in its endeavors (Grant, 2005) and General Motors suffered similarly with around $19 million in liquid assets frozen during the panics (Lumley, 2009, p.141). The other great manufacturer, Chrysler, relied heavily upon bank loans from Detroit banks, with $19 million outstanding in 1933. The extent to which Chrysler suffered can be seen from estimates of its exposure to the disruption. In April 1933, the *Wall Street Journal* reported:

> Chrysler's balance sheet for March 31 discloses further declines in cash and its equivalent and in working capital during the quarter...[and]...the drop in liquid strength is due entirely to the segregation of deposits in closed or restricted banks from working capital... Chrysler's net cash position has declined $10,039,611 since March 31, 1932, a decrease of which $6,520,504 was directly caused by the banking crisis.

Our identification strategy exploits the fact that at least some bank financing was local even for large, publicly traded firms. This allows us to disentangle the effects of finance from aggregate demand shocks that were also likely to have played a role in affecting real economic activity during this time period.

III The Data

III.A Measuring Innovation

Our data are based on all firms in the National Research Council's 1921, 1927, 1931, 1933 and 1938 editions of *Industrial Research Laboratories of the United States*. The NRC began an extensive program of direct correspondence with firms operating R&D facilities after the First World War, as part of its efforts to codify information on the location of laboratories and scientific personnel. The NRC data cover publicly traded and private firms so we observe close to the universe of firms in the R&D sector over this period, absent of firm size or ownership censoring. In fact, the NRC data are considered to be the most comprehensive guide to R&D activities for any period in U.S. history. Although much prior research has examined innovation using the NRC surveys, especially work by Mowery (1995, 2005), Mowery and Rosenberg (e.g., 1989, 1998) and by MacGarvie and Furman (2007, 2009), our novel micro data stems from the fact that we match the underlying firm-level data recorded in the NRC to other key datasets.

We first match the database of NRC firms to firm-level assignees in U.S. patent data.[5] It is thus possible to create an annual proxy for R&D activity for each firm. Although the relationship between R&D and patenting is not exact, Griliches (1990) finds a close temporal correlation between R&D expenditure and patents so changes in inputs and outputs should be correlated. Our patent data are measured as of their application date so we have a close association between the timing of patents and the timing of R&D.[6] Of course, not all inventions are patented and the propensity to patent varies strongly across industries (for example, higher in areas like machinery and machine tools than the food industry). But an advantage of our data is that the propensity to patent was very high by modern standards so historical patent metrics should be an economically meaningful measure of innovation. In addition, since industry-specific differences in the propensity to patent remained constant during the 1920s and the 1930s (Nicholas, 2011) our use of industry fixed effects appropriately controls for these time invariant differences.

An increase in distress to the financing environment for firms could lead to a fall

[5]This part of the data construction process is explained in more detail in Nicholas (2011).

[6]Other proxies of R&D such as the employment of research personnel are available from the NRC surveys, albeit in the years when the surveys of the labs were undertaken.

in the quantity, quality and novelty of patenting, if firms were forced to innovate in a manner constrained by access to external finance. To examine patent quality, we use citations to patents granted between 1947 and 2008 to adjust patents according to their technological significance. Following Trajtenberg (1990), the idea of using citations to adjust patent counts for quality is common in the literature. Kogan et. al., (2012) construct a useful alternative indicator of patent quality by looking at the stock market reaction to patents for the time period 1926 to 2010. Their measure is strongly correlated with citations. Our citations dataset includes almost 43 million forward citations to patents granted since 1836 in the population of patents granted between February 1947, when citations were first officially incorporated into patent documents, and September 2008 (Nicholas, 2010). Furthermore, the patent citation trail allows us to calculate patent novelty measures - *originality* and *generality*. Because *originality* is typically constructed using backward citations (but these are unavailable in our data because our citations start in 1947) we use a proxy measure that codes a patent as 1 if it is the originating patent in a citation trail and 0 if earlier patents are cited. *Generality* measures the range (by USPTO 3-digit classes) of later generations of inventions that benefit from an early patent so it can be thought of as an indicator of a patent's future scope.[7] Both *originality* and *generality* measures can be used to determine the extent to which firms were being risky or conservative in their pursuit of R&D.

We also geocode the address of each firm in the dataset, in order to determine the county in which it was located. For firms operating multiple R&D labs in different geographies, we set the location of the firm's headquarter.[8] We then matched the county in which the firm was based to county-level bank data from the FDIC. An attractive property of the FDIC data is that it covers all banks, not just banks that were members of the Federal Reserve System. Failure rates were much higher for nonmember banks and the change in the loans on their balance sheets also fell more sharply during the 1930s (Wicker, 1996, p.15). Consequently, we are able to create an accurate measure of distress to the local banking market where the firm was based.

[7] *Generality* is defined as one minus the Herfindahl index of patent citations by 3-digit class. We use the bias-adjusted measure of *generality* described in Hall (2005).

[8] 16 percent of firms in the NRC data operated multiple labs. One example is General Electric where the main center of R&D was Schenectady in upstate New York.

Finally, we identify a set of firm and industry-specific measures that serve as important covariates in our regressions. We sort firms into industries using descriptions of the R&D activity they undertook. Also, we code publicly traded firms as those listed in the *Commercial and Financial Chronicle*, which tracked stocks traded on any exchange in the United States, not just the NYSE.

Descriptive statistics for our data are reported in Table I for the firms that we use in our empirical analysis. Of the 2,777 firms listed in the NRC volumes we excluded those without full information on R&D activity. We also excluded firms whose first entry in both the NRC survey and the patent data was after 1931. This is to ensure that our difference-in-differences specifications use firms that existed both before and after our event year so that our results are not confounded by entry and exit.

It can be seen that the 2,064 firms in our sample accounted for over 140,000 patents from 1920 to 1938.[9] Table I highlights that although publicly traded firms accounted for 13 percent of firms, they accounted for 45 percent of patents. The propensity to patent was also higher for publicly traded firms, with around 60 percent of all firms in the NRC data patenting compared to a propensity to patent of almost 90 percent for NRC firms listed on the public markets (Nicholas, 2011). Publicly traded firms patented more, so they accounted for more citations, but the average number of citations per patent was also higher, suggesting that these firms also produced higher quality innovations on average. They also tended to produce patents with higher average *originality* and *generality* scores so the impact of their citations on subsequent patents was both stronger and broader.

The industry distribution of NRC firms mirrors trends in innovation during the early twentieth century. Electricity became a dominant R&D-based industry with the electrification of homes and manufacturing establishments (David, 1990, Atkeson and Kehoe, 2007), while the chemicals industry also flourished in an environment of knowledge diffusion and rapid technological change (Mokyr, 2002; Murmann, 2003). Machinery, automobiles and communications also rank as industries of particular significance during the 1920s and the Depression years (Bernstein, 1989; Szostak, 1995).

[9]Since the 1921 survey was conducted during 1920 we also include this year in our analysis.

III.B Measuring County-Level Bank Distress

The principal explanation for the widespread bank failures of the 1930s was developed by Friedman and Schwartz (1963) who argued that bank failures were driven largely by banking panics that led to the widespread failures of otherwise healthy banks.[10] They document that the most extreme failures for banks occurred in a window of time between 1930 and 1933. In particular, they identified four panics: in the Fall of 1930, the Spring of 1931, the Fall of 1931 and the first quarter of 1933 which culminated in Roosevelt's decision to declare a national banking holiday in March 1933. Data from *Banking and Monetary Statistics* is consistent with this view, showing that the volume of loans fell by half during this three year period.

To measure bank distress, we use FDIC county-level data on banks in the United States between 1920 and 1936 and the first Friedman-Schwartz crisis in 1930 to establish an event date for observing pre- and post-period differences in banking sector distress. While the FDIC data treat failures and suspensions synonymously (and the two are distinct because suspended banks could subsequently re-open), Calomiris and Mason (2000) argue that this issue does not make a substantive difference when identifying bank distress empirically. We rely on distinguishing counties that were differentially affected by bank distress, so we calculated a bank distress intensity score for each county c, scaling the number of bank suspensions between 1930 and 1933 by the number of banks in existence in 1929.

$$DISTRESS_c = \frac{\sum_{t=1930}^{t=1933} SUSPENSIONS_{c,t}}{BANKS_{c,\ 1929}}$$

Figure 2A shows the geographic distribution of high fail and low fail counties across the United States, coding counties with above median bank distress as high stress, and those below as low stress. It illustrates the broad spatial pattern of distress with some concentration in Midwestern counties. Failures were initially highly concentrated in rural

[10] In their view, panic and contagion exogenously caused failures and banks failed because they were illiquid as opposed to being insolvent. Others, however, have argued that insolvencies played a much larger role in explaining the pattern of bank failures (Temin, 1976; White, 1984; Calomiris and Mason, 1997, 2003). Bringing together both sides of the debate, Bordo and Landon-Lane (2010) find a crucial role for methodology. Studies using macro data tend to find illiquidity effects. Those using micro data tend to find evidence in support of insolvency.

communities as a consequence of negative shocks to agriculture, but as the banking crisis deepened, urban areas became more affected (Wicker, 1996, p.7). Brocker and Hanes (2012) show that cities experiencing the largest run ups in real estate prices during the early-to-mid 1920s also suffered the greatest declines during the 1930s. If lower real estate values depressed demand or mortgage defaults led to declines in credit supply, this would be another potential source of spatial heterogeneity in bank distress.

Figure 2B shows the corresponding location of firms in our data, revealing a strong preponderance of R&D activity in manufacturing areas of the North East. Despite some level of spatial concentration, however, it can be seen from both figures that there is evidence of sufficient variation in the extent of bank failures across counties where R&D firms were located to make this an attractive source of data to exploit for identification.

IV Estimation Strategy and Main Results

IV.A Reverse Causality and Sorting

Assuming the Friedman-Schwartz view of banking panics is correct, banks failed because of panic disturbances rather than weaknesses in bank fundamentals. Banks, they argue, were illiquid not insolvent and therefore with exogenous panics our estimates should approximate the true effect of bank sector distress on innovation. Even Calomiris and Mason (2003), who show that variation in local demand conditions may have played a role in local bank failures, find that the lagged liabilities of failed businesses that were borrowing from banks do not predict bank failures. Extrapolating from their results to ours suggests that the performance of R&D firms in our dataset is unlikely to be a source of endogeneity when explaining bank sector stress.

Nevertheless, we provide additional evidence to show that reverse causality is not a serious concern. We estimate in Appendix Table I that the level of bank finance by publicly traded R&D firms in our dataset was around 2 to 3 percent of banks' outstanding loans, implying that, on average, the poor performance of any individual publicly traded firm would not have led to the bank failures in their local county. At the same time we also identify in Appendix Table II a strong effect of bank distress on the balance sheets of publicly traded firms. For NRC firms that we were able to trace in *Moody's Manual of*

Industrials, we find a one standard deviation change in our bank distress intensity score (specified as a normalized mean zero standard deviation one variable) is associated with a 4 percent decline in notes payable and bank loans and an 8 percent decline in cash in the post-period. Our evidence implies that, on average, NRC firms could not have caused banks to suspend their operations in local markets, but that bank distress in local markets did negatively affect the financial position of R&D firms.

We also rule out that more productive firms in our dataset were systematically more likely to "sort" on "better" counties and therefore locate in counties that ultimately experienced fewer bank failures. Figure 3A plots firm patenting between 1921 and 1929 against the severity of the bank distress between 1930 and 1933. It shows that there is no systematic relationship between the innovation of firms in the pre-period with the level of bank failures experienced by counties in the post-period. In Figure 3B, we use firm sales as a non-innovation measure of firm performance. This data is less comprehensive than the patenting data we have due to limitations on what firms reported to *Moody's*. But again, we find no evidence that weaker firms were systematically sorting into counties that later experienced more bank failures.

In the following sections we report three main sets of results. First, we compare innovation by private firms to public firms, since we would expect private firms to be impacted more by rising costs of bank intermediation than public firms. We view these results as being largely descriptive evidence that is consistent with bank distress stifling innovation, since it is likely that our comparison of private and public firms would be confounded by the effects of local aggregate demand shocks that might disproportionately hit private firms. The second and third sets of results, which we view as the core of our analysis, focus only on publicly traded firms. We maintain that publicly traded firms sold into national markets and therefore faced similar aggregate demand within industries, but the local nature of bank financing at the time implied that the degree of bank stress they faced varied by the county in which they were located. For these firms we can disentangle the effect of bank stress on innovation from the confounding role of aggregate demand. If our hypothesized channel is the reason for our findings rather than omitted variables, we should expect to see stronger results for those firms operating in industries

more dependent on external finance. Hence, we examine whether firms engaged in R&D in more capital intensive industries were disproportionately influenced by bank distress. We use Rajan and Zingales' (1998) measures to categorize firms in our dataset as being more, or less, dependent on external finance (Appendix Table III provides the concordance we use to map the Rajan and Zingales industries to the ones in our data) .

IV.B Private Firms versus Publicly Traded Firms

To frame our first set of results, Figure 4A plots an index of patenting per firm, grouped by public and private firms. Note that the growth in patenting by public and private firms is relatively similar until 1930 after which there is divergence. The trend in patenting by public firms flattens in the 1930s, whereas patenting by private firms falls over this period, with the divergence in patenting between the two groups of firms being particularly sharp in the period 1930 to 1933, which experienced the most dramatic bank distress.

In order to examine this relationship in a multivariate context, we use differences-in-differences. Table II reports coefficients from the following OLS specification:

$$Log(PATENTS)_{f,t} = \beta_1 PRIVATE_f + \beta_2 PRIVATE_f \times POST_t + \phi_c + \tau_t + \psi_i + \epsilon \quad (1)$$

Here, $Log(PATENTS)_{f,t}$ is the log-transformed patents granted to firm f measured as of the application year t. The parameters ϕ_c, τ_t and ψ_i correspond to county, year and industry fixed effects, respectively. Standard errors are clustered at the county level. Our main variable of interest is $PRIVATE_f \times POST_t$ the interaction between a dummy variable coded unity for private firms and a dummy variable coded unity for the post-period. The coefficient β_2, or more specifically $[exp(\beta_2)-1]\times 100$, measures the percentage change in patenting by private firms, relative to public firms, in the post-period.

Column (1) of Table II shows that private firms experienced a 27 percent relative decline in the number of patents filed in the post-period. While column (1) is estimated across all firms in our sample, regardless of whether or not they patented, column (2) restricts the sample to firms that had patented at least once in the sample period. As can be seen from column (2) of Table II, the coefficient is almost identical, implying the results are not due to compositional differences across counties where more actively patenting

firms were based.

In columns (3) and (4) of Table II, we estimate specifications with citations measures as a dependent variable. We use total citations to patents per firm year and average citations per patent per firm year to proxy for patent quality.[11] Total citations to all patents filed by private firms in the post-period were 45 percent lower relative to the citation difference between private and public firm patenting in the pre-period. If firms cut back on marginal patents, we might expect average citations per patent to stay the same or even rise. On the other hand, if firms undertook less radical and novel R&D, and focused instead on incremental innovation, we would expect citations per patent to fall. As can be seen from column (4), citations per patent by private firms fell by about 23 percent in the post-period relative to the pre-period, suggesting that firms undertook more incremental innovations during the 1930s.

In columns (5) and (6) we further investigate the hypothesis that private firms may have been undertaking less radical innovation, by using measures of the *originality* and *generality* of the patents they filed. Columns (5) and (6) reveal that patents filed by private firms were systematically less original and had a systematically lower impact on subsequent innovation. Table II therefore provides consistent evidence, using several distinct measures, that innovation by private firms was both lower and less novel during the Depression era.

IV.C Focusing on Publicly Traded Firms

Given that the Great Depression was associated with a reduction in aggregate demand, one explanation for the results in Table II is that non-financial factors could have affected private firms more than publicly traded firms. If this was the case, the descriptive patterns we outline in Table II could not be attributed to bank distress *per se*. Therefore, we focus on publicly traded firms to disentangle the role of aggregate demand from the effect of the credit shock. Both private and public firms relied heavily on their local banking markets for access to a supply of R&D capital, but publicly traded firms were more likely to sell their products into national markets. We therefore exploit the fact that public firms in the same industry faced the same shocks to aggregate demand but a differential effect on

[11] Citations refer to the cumulative citations (1947 to 2008) to patents filed by firm f it year t.

their access to finance, depending on the degree of bank distress in the county in which they were located. In doing so, we can use cross-sectional differences in bank suspension rates across counties to examine how the severity of the shock to bank finance faced by the publicly traded firms impacted their rate and trajectory of innovation.

Figure 4B plots the raw data of patenting for public firms located in more versus less distressed counties, as an illustration of our main finding. It shows that firms located in more distressed counties experienced a sharp decline in patenting in the post-1929 period relative to those located in less distressed counties. As in Figure 4A, the bulk of the difference in these two samples is driven by changes that occurred in the 1930 to 1933 period, which was when the vast majority of bank failures occurred. In order to probe the data further, we use the following specification:

$$Log(PATENTS)_{f,t} = \gamma_1 STRESS_c \times POST_t + \phi_c + \tau_t + \psi_i + \epsilon \tag{2}$$

Here, we keep the same set of fixed effects as before, but we introduce $STRESS_c \times POST_t$ as the main variable of interest. That is, we interact our cross-sectional measure of bank distress at the county-level with a $POST$ dummy variable that takes a value of unity from 1930 onwards. County fixed effects capture systematic differences in the lending environment across counties (such as number, or the competitive environment of banks, as well as the main effect of bank distress) that may affect access to finance for firms. Year fixed effects and industry fixed effects control for systematic differences in loan characteristics and fluctuations in aggregate demand that might vary systematically across these industry types or across years. Our estimations therefore examine whether publicly-traded firms located in counties that experienced higher levels of bank distress experienced greater declines in innovation compared to those located in less-stressed counties. For ease of interpretation we normalize our bank distress intensity score to have zero mean and unit standard deviation.

Column (1) of Table III shows that publicly-traded firms in counties with higher levels of bank distress were less likely to patent in the post-1929 period relative to those located in less distressed counties. The coefficient implies that a one standard deviation increase in the number of bank suspensions was associated with a 7 percent decline in the

rate of patenting by firms in the post period. For our other measures, patent citations, *originality* and *generality*, we cannot reject the hypothesis that the trajectory of innovation by publicly-traded firms was any different in the post-period than the pre-period.

In order to test for confounding trend influences, we also estimate time varying effects of bank distress by interacting our normalized bank distress intensity score with a set of year dummies measured relative to a base year of 1929. The coefficients from these regressions and their confidence intervals are plotted in Figures 5A and 5B. Before the Friedman-Schwartz bank panic window, all the coefficients are statistically insignificant from zero at the customary level, whereas they drop noticeably for patents and citations during the post-period. The time varying predictors suggest causation ran from bank distress to observed declines in the level of R&D output, but they also highlight that the effects were concentrated during the early years of the Great Depression.

IV.D The Role of External Finance

To probe the results further, we examine whether there are differential effects for firms operating in more versus less capital intensive industries. From a substantive perspective, this helps to isolate the channel through which we believe bank distress might have affected innovation and it also improves the robustness of our identification. For example, it is still possible that other more local factors such as the presence of skilled scientists, institutions such as universities or agglomerative forces might affect both county-level fundamentals and innovative output. Firms located in more distressed counties may have faced tougher labor markets with respect to hiring and retaining talented scientists compared to those located in less distressed counties.

Table IV suggests that the effect of banking sector distress on technological development we have observed so far was especially severe and only pertinent for firms operating in capital intensive industries. We use the same specifications from Table III, but partitioned by firms in industries that were more or less dependent on external finance and we test for significant differences between the coefficients using Wald tests.[12]

[12]We establish a concordance between industries in which the NRC firms were active and those reported by Rajan and Zingales (1998). Although the Rajan-Zingales external finance dependence measures pertain to firms from the 1980s, we follow the intuition, as well as Mitchener and Wheelock (2010), and assume persistence across time. In support of this assumption, we verified that the correlation between these measures and a proxy measure for firms in our data during the 1920s and 1930s is strong. Rajan and

Column (1) of Panel A shows that the decline in patenting for firms that depended on external finance was 19 percent lower in the post period for a one standard deviation increase in bank distress. On the other hand, for firms in industries less dependent on external finance, the difference between firms in more versus less distressed counties is economically much smaller and not statistically different from zero. Wald tests of the coefficients across high and low dependence firms indicate statistically significant differences at the customary levels. We find the same pattern of results in panels that use citations counts and citation counts per patent as dependent variables, implying that bank distress had an effect on the quality of technological development.

Additionally, we find that high finance dependence firms in worse hit counties produced significantly less novel patents by their *originality* and *generality* scores, which we interpret as evidence that the presence of bank distress was particularly detrimental to firms engaging in high-risk R&D projects. While the coefficients in Table III imply the aggregate effects of bank distress on publicly traded firms was economically limited, Table IV highlights that effects are considerably stronger when considering differences between firms in capital intensive and less capital intensive industries.[13] For firms in capital intensive industries we find strong evidence of substantial declines in the quantity, quality and the novelty of their patenting.

V Robustness Checks and Mechanisms

V.A Instrumental Variables

Our identification thus far has been based on the premise that publicly traded firms sold into national markets and hence would have faced similar aggregate demand shocks but

Zingales calculate the level of dependence using capital expenditures minus cash flow from operations over capital expenditures, while we use bank notes payable over fixed assets. This proxy measure, which we constructed by tracing all the firms listed in the NRC surveys that were also listed in *Moody's Manual of Industrials*, has a correlation coefficient with the Rajan-Zingales measure of 0.28 across all sectors.

[13]In Appendix Table IV, we replicate the results from Table IV using our proxy variable outlined in column (3) of Appendix Table II. Appendix Table 3 shows that we get consistent results using a measure of external finance dependence based on the contemporaneous period. We see that the pattern of fewer patents that are incremental continues to be prevalent in industries more dependent on external finance, although the results from the Wald tests are slightly weaker for the citation measures.

Firms' reliance only on bank finance during this period is clearly endogenous. Appendix Table IV is therefore meant only to provide suggestive evidence that is consistent with the patterns from the Rajan and Zingales measure, which in turn is exogenous to the sample of firms in our analysis.

depended on financing that was impacted by local shocks in credit supply. A concern with our results is that variation in aggregate demand shocks may still have impacted some firms and banks more than others, in a way that led firms in more stressed counties to be systematically less likely to innovate. Although segmenting our sample by more versus less capital intensive industries does help to address this particular issue, we present another test, using instrumental variables to separate out the supply side effect of bank distress from aggregate demand shocks.

Our strategy is based on the literature that documents a strong relationship between a community's social structure and the propensity to drive banking panics.[14] The basic intuition is that more fragmented communities are less likely to trust each other, and hence may be more likely to propagate a bank run through simultaneous bank withdrawals in the face of a perceived liquidity crisis. In order to derive a measure of the cohesiveness or fragmentation of the social structure in a county, we draw on data from the 1906 Census of Religious Bodies, one of the most complete censuses ever conducted on religious entities in the United States.[15] This census provides county level data on the membership at one of ninety one different religious denominations. Church descriptions highlight fragmentation by immigrant status (e.g., Armenian, Greek, German, Polish churches among many others), religion (e.g. Japanese Buddhist or Jewish churches) as well as race (e.g., African Methodist church). Our instrument is based on (one minus) a county-level Herfindahl index of religious concentration using the share of the county's population that is affiliated with each of these religious organizations. Thus, it represents a measure of religious fragmentation in each county.

The exclusion restriction requires that religious fragmentation in 1906 did not affect the rate or trajectory of patenting by the firms in our sample, other than through the impact on bank stress in the post period. This premise is supported by the fact that we

[14]For example, Kelly and O Grada (2000) find that the social networks of Irish immigrants to New York played a crucial role in the panics of 1854 and 1857. As they put it, "[d]epositors from one set of counties tended to close their accounts in both panics, while otherwise identical individuals from other counties tended to stay with the bank" (p. 1123). Iyer and Puri (2004) find that "[s]ocial networks matter - if other people in a depositor's network run, the depositor is more likely to run" (p. 1416).

[15]Surveys were conducted in 1906 and at ten year intervals until 1936. The 1936 census is generally regarded to be seriously incomplete. There are also issues in the 1916 and 1926 surveys, where the definition of "church membership" was often manipulated to inflate membership rates (Christiano, 1984). For our purposes we view the 1906 survey as being the most reliable.

find no correlation between our measure of fragmentation and the level of firm patenting in the pre-period. We therefore estimate two stage least squares regressions, where bank stress in a county is instrumented with the degree of religious fragmentation in that county. Column (1) of Table V reports the result of the first stage regression:

$$STRESS_c \times POST_t = \theta_1 FRAG_c \times POST_t + \phi_c + \tau_t + \psi_i + \epsilon \quad (3)$$

where the set of fixed effects is the same as in equation (2) above. Since we include county fixed effects in all our specifications, we instrument for the interaction between bank distress and the post-period. We do this using an interaction between our index of religious concentration and the post-period dummy.

Column (1) of Table V documents a strong positive first stage relationship between the degree of fragmentation in the county and county level bank stress in the post period. The partial R-squared of $FRAG_c \times POST_t$ is 0.09 and the F statistic is 11.32.

Columns (2) to (7) report the results of two stage least squares regressions where the dependent variable is regressed on the predicted values of $STRESS_c \times POST_t$ derived from the first stage, along with the full set of fixed effects, as in Table IV. For both patenting and citations to firm's patents, we show the instrumented effect of bank distress in the full sample, and in the sub-samples of industries that are more versus less dependent on external finance. Consistent with the findings in Table III, we find moderate effects of bank distress on innovation in aggregate and consistent with Table IV the results are much stronger in capital intensive industries compared to those in less capital intensive industries. Our regressions using *originality* and *generality* as dependent variables follow a similar pattern although the point estimates are imprecisely estimated and do not have statistical significance.[16]

Overall, our findings when instrumenting for bank distress provide further evidence to suggest that local shocks to the supply of capital, as opposed to demand-side factors, had a substantive impact on innovation for firms in more capital intensive sectors.

[16]For industries with high dependence on external finance, the coefficients and standard errors (in parentheses) are -0.081 (0.106) for *originality* and -0.052 (0.065) for *generality.* For industries with low dependence on external finance, the coefficients and standard errors are 0.025 (0.029) for *originality* and 0.005 (0.027) for *generality.*

V.B County-by-year Fixed Effects

To further reinforce our main result in Tables IV and V, we address concerns that time-varying differences across more versus less distressed counties may still account for our results. For example, more distressed counties may react to crises differently from less distressed counties in a manner that interacts with capital intensive firms. We attempt to rule out any time-varying confounding effects at the county-level by exploiting a triple differences estimator that uses county-by-year fixed effects. It takes the following form:

$$\begin{aligned} Log(PATENTS)_{f,t} &= \delta_1 HDEP_i \times STRESS_c \times POST_t + \delta_2 HDEP_i \times STRESS_c \\ &+ \delta_3 HDEP_i \times POST_t + (\phi_c \times \tau_t) + \psi_i + \epsilon \end{aligned} \tag{4}$$

We use the same set of dependent variables, but we specify a variable for our normalized bank distress score interacted with the post-period dummy and a dummy variable coded unity for firms active in capital intensive industries. Our county-by-year fixed effects, $(\phi_c \times \tau_t)$, absorb any fixed or time-varying differences across counties, including the main effect of $STRESS_c$ and the interaction of $STRESS_c \times POST_t$. Our main variable of interest, $HDEP_i \times STRESS_c \times POST_t$ examines if firms in capital intensive industries experienced a greater decline in innovation in more stressed counties in the post-period.

While this more demanding specification reduces the number of "effective" observations because we are identifying off firms operating in the same county in the same year but in more versus less capital intensive industries, the results in Table VI again show strong evidence of the link between financial sector disruption and innovation. Coefficients on the triple interaction term in Table V show that firms in capital intensive industries experienced a 25 percent drop in patents, and a 14 percent drop in citations per patent in the post-period relative to otherwise equivalent firms in the same county in less capital intensive industries. Furthermore, the effects on *originality* and *generality* are large relative to the sample means shown in Table I.

V.C R&D Inputs and Mechanisms

Next, we illuminate the mechanisms that plausibly account for our results. We have argued that bank distress not only impacted the rate, but also the trajectory, of innovation

meaning that firms in distressed counties were more conservative in the innovation they pursued and the types of R&D projects they undertook. The large negative effect of bank distress we find on citations to patents and especially on our measures of patent *originality* and *generality* is consistent with firms cutting back on exploration around radically new innovations in favor of incremental technologies (e.g., Chava et. al., 2012).

To test for supporting evidence for this interpretation of our findings we examine the extent to which bank distress impacted innovation through the use of R&D inputs versus a change in the way in which inputs were deployed.[17] Although the NRC surveys provide only periodic information on R&D inputs, we can use data on the number of research workers and research laboratories as alternate dependent variables. The results in Table VII show that among publicly traded firms there is some indication of a decline in research employment and research laboratories, particularly among firms operating in more capital intensive industries. However, the declines are not as strong, or as precisely estimated, as the declines we observe in both the rate and the trajectory of patenting. Notably, Wald tests for the difference in coefficients for firms in more versus less capital intensive industries are not statistically significant.

Finally, we also show in Appendix V that our main results for citations per patent and for our measures of *originality* and *generality* continue to hold even when we condition on firms' use of R&D inputs. Although this evidence is suggestive, since the level of inputs is clearly endogenous, it does highlight that the trajectory of innovation was different when considering input variation.

VI Discussion and Conclusion

The Great Depression witnessed unprecedented distress to the U.S. banking system, so it serves as a useful environment for understanding linkages between finance and real economic outcomes. Thousands of banks either failed, or suspended their operations within a short time period, putting enormous stress on firms that depended on external

[17]This question is related to the controversial literature on labor hoarding. Bernanke and Parkinson (1991) make the case for labor hoarding as an explanation for the pro-cyclicality of labor productivity where firms hoard labor during downturns in order to avoid high short-run adjustment costs. If labor hoarding applied to R&D firms during the Depression years we would expect that adjustment to the effects of bank distress would be more clearly observable on output margins (i.e., through patents) rather than input margins (i.e., through research employment).

finance. After the 1929 stock market crash, firms were limited in their ability to raise public equity and debt finance, so the reliance on cash flows and bank-financing was much greater than it had been during the 1920s. Moreover, branch banking regulations meant that the experience of local banks was closely tied to the circumstances of firms at the county-level.

We have provided new data on finance and innovation for a period that we still know very little about and we have used an empirical framework that establishes a relationship between the effect of local bank distress and the inventive activities of R&D firms. Our results contribute to the growing literature relating the financing environment to firm-level innovation and to the literature examining how the structure and provision of finance during the Great Depression affected the performance of the economy. We find negative effects of bank distress on innovation, especially for firms operating in industries that were more dependent on external finance. We also find that bank distress negatively impacted the type of R&D undertaken, with a shift away from risky and towards more conservative projects in highly distressed counties. This suggests that the real effects of the financial sector are not restricted to the level of firm innovation, but can have an immediate and longer run effect on the trajectory of innovation that firms choose to undertake.

Despite finding an effect of bank distress, our results also help to shed light on accounts suggesting that some firms could access capital during this time. For example, the chemicals industry giant, DuPont, invested over $1 million on R&D between 1931 and 1934 in research designed to commercialize the science of new synthetic fibers (Scherer, 1984, p.4). By 1937, 40 percent of DuPont's sales came from products that did not exist before 1929 (DuPont, Annual Report, 1937, pp.12-13). Other accounts of technological activity during this period find that R&D employment increased almost threefold between 1933 and 1940 (Mowery and Rosenberg, 1998), while according to Field (2003, 2011) the productivity statistics imply that many firms continued to expand R&D even though access to external finance was severely constrained.

Two aspects of our analysis help to reconcile the negative and positive effects. First, publicly traded firms conducted a large share of overall innovation in this period, and furthermore, it was only R&D firms operating in capital intensive industries in the most

stressed counties that seemed to have been disproportionately affected. Importantly, we do not find a statistically significant association between bank sector distress and innovation for firms with lower levels of capital requirements. Of the 2,064 firms that we use in our empirical analysis, 46 percent were located in counties with above median bank distress, but only 13 percent were also active in capital intensive industries.

Second, Figures 4A, 4B, 5A and 5B show that the effect of bank stress on innovation was strongest in the years immediately after the collapse of the banking sector but the effects attenuated as the Depression years progressed. Figures 5A and 5B suggest that the quantity and quality of patenting by firms operating in more stressed counties approached the level of those in less stressed counties by the end of the decade. Larger, publicly traded firms may have been able to recover from the effects of bank distress by tapping into the public markets by the late 1930s.

Both of these factors have implications for our understanding of the Great Depression. While we have identified a negative relationship between bank distress and innovation, we can also explain why the worst financial crisis in U.S. history did not inhibit productivity growth from technological change as much as might have been expected.

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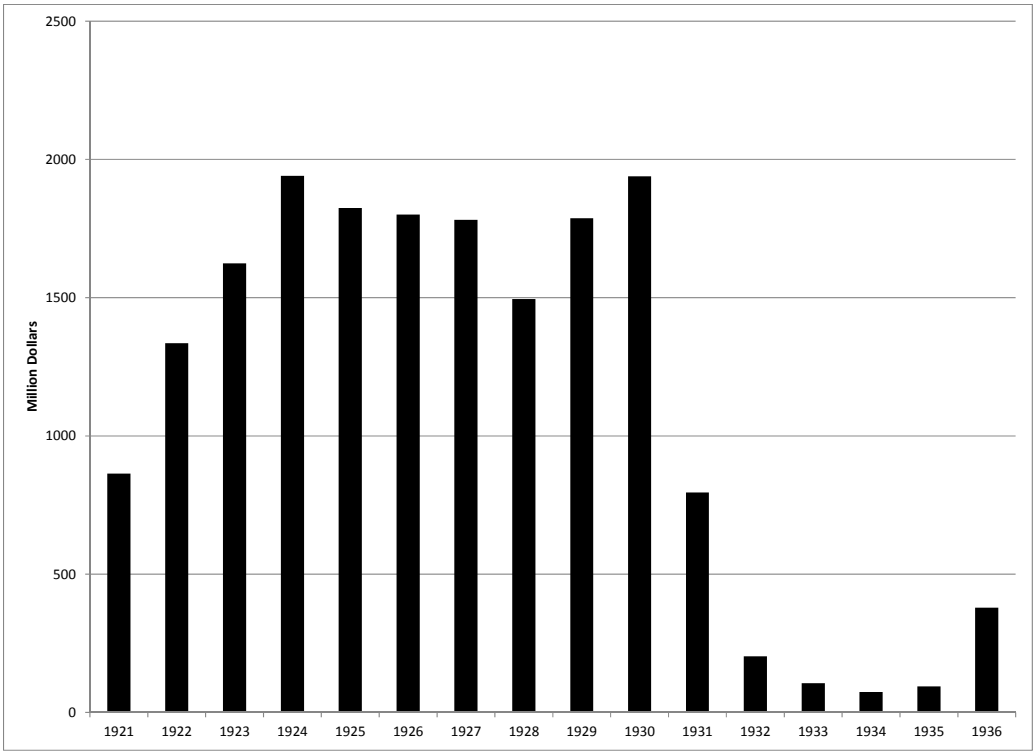
Figure 1. Moody's Investors Service, New Issues of Stocks and Bonds



Notes: This figure plots data on new corporate productive issues of stocks and bonds, as reported by Moody's investor service in George Eddy (1937), "Security Issues and Real Investment in 1929", *Review of Economics and Statistics*, XIX, p. 91

Figure 2A. The Location of Bank Failures

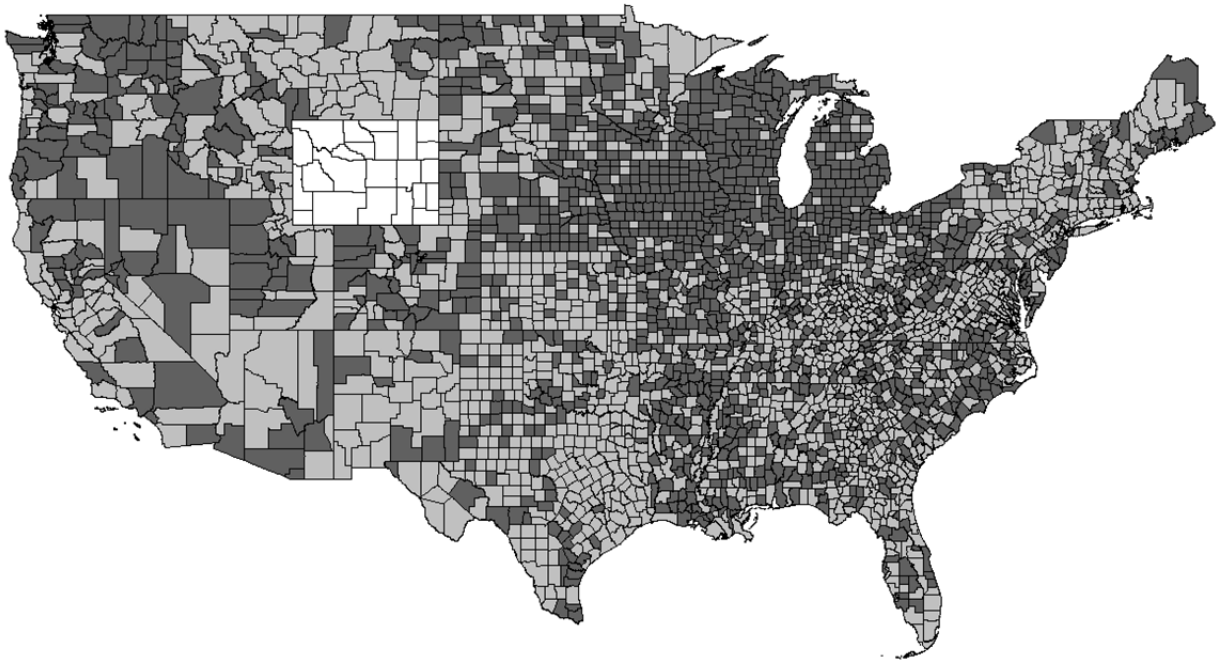
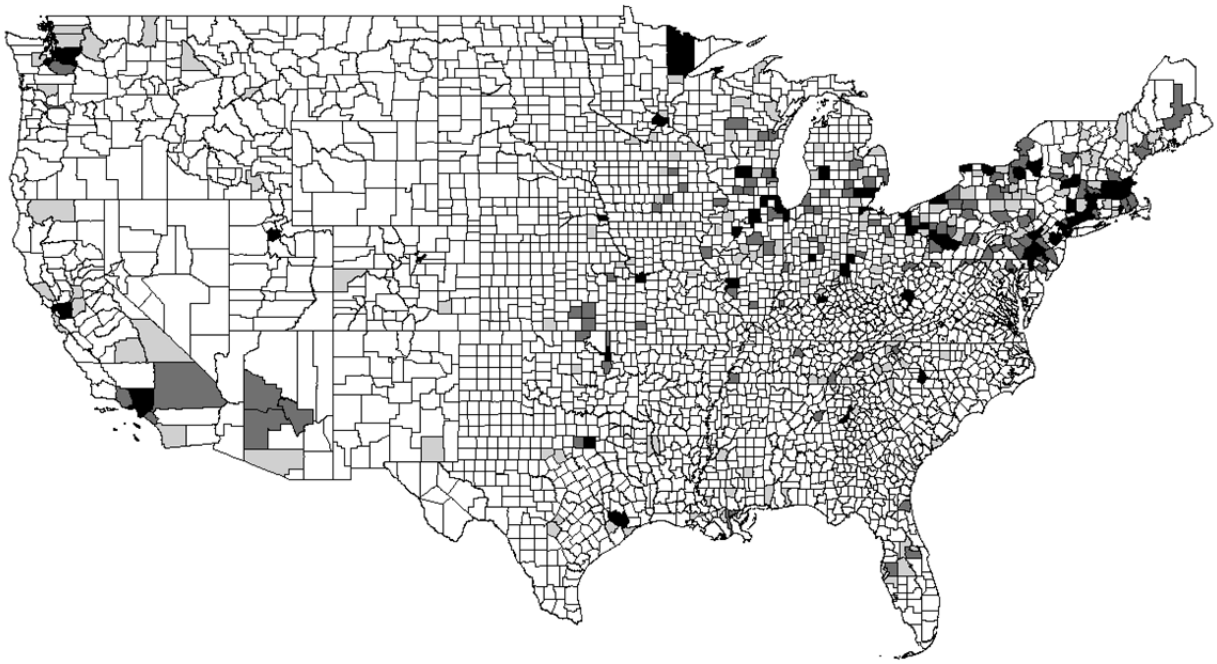


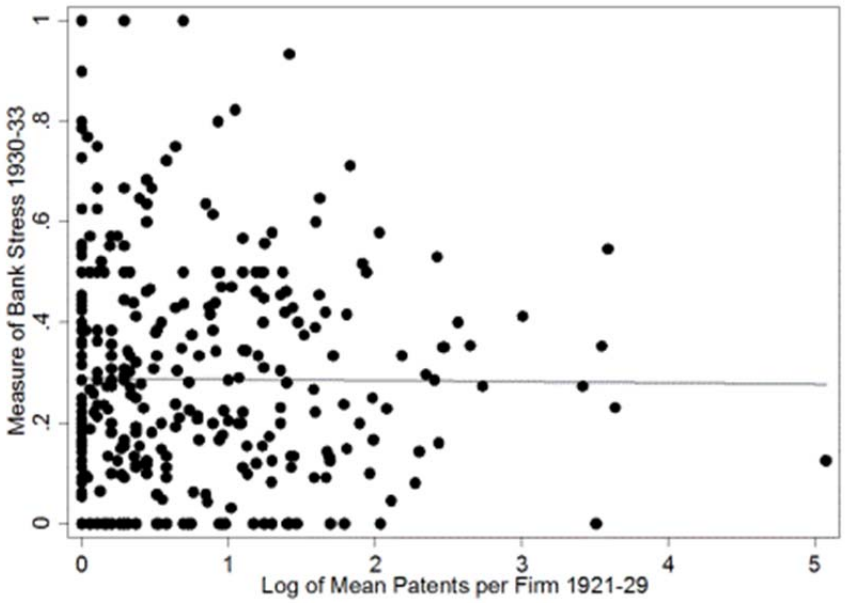
Figure 2B. The Location of R&D Firms



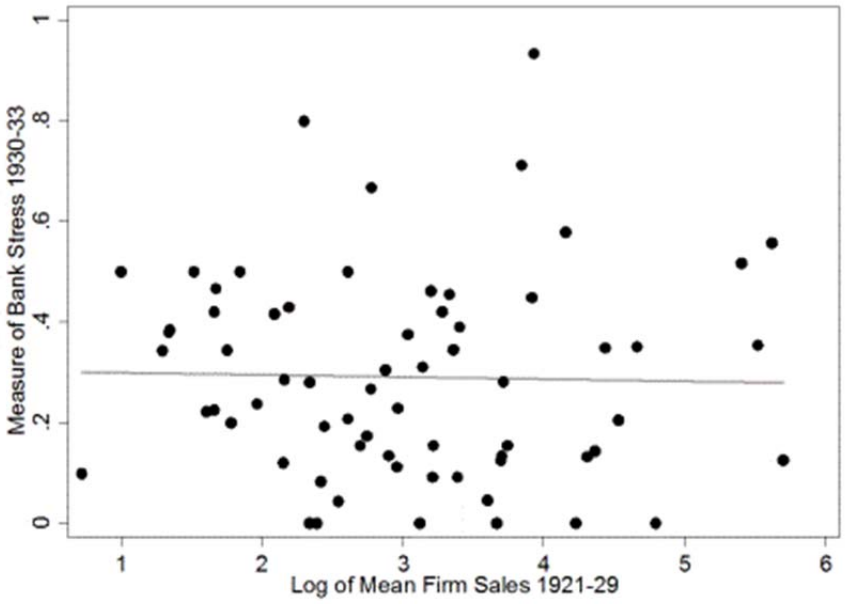
Notes: Bank failures are coded as >50th percentile (dark grey) or <=50th percentile (light grey) according to the ratio of the number of bank failures in a county 1930-33 to the number of banks in a county in 1929. FDIC bank data does not cover Wyoming. R&D firms are categorized at three levels: 1 firm per county (light grey); 2-5 firms per county (dark grey); more than 5 firms per county (black).

Figure 3. Testing for Sorting of Firms into Counties

A. Patents



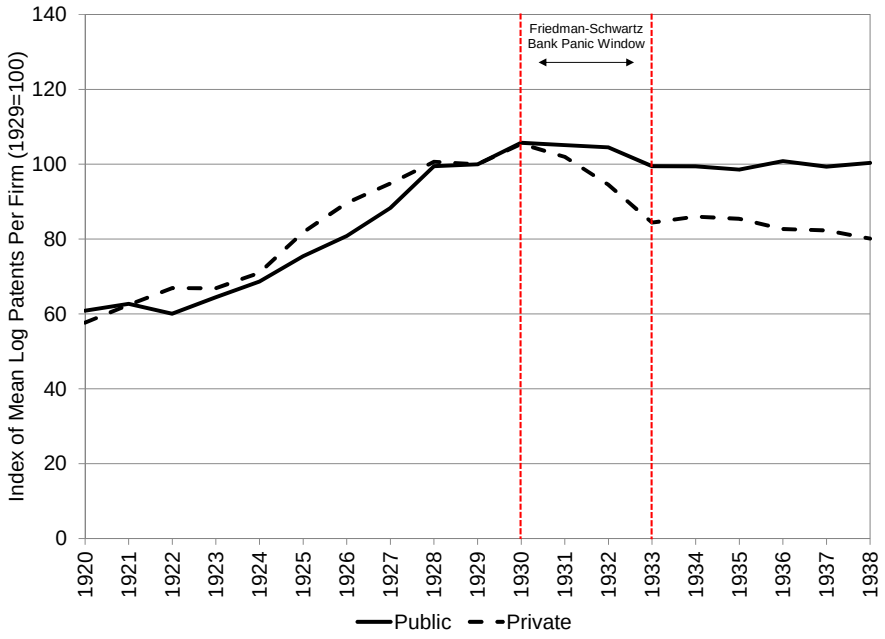
B. Firm Sales



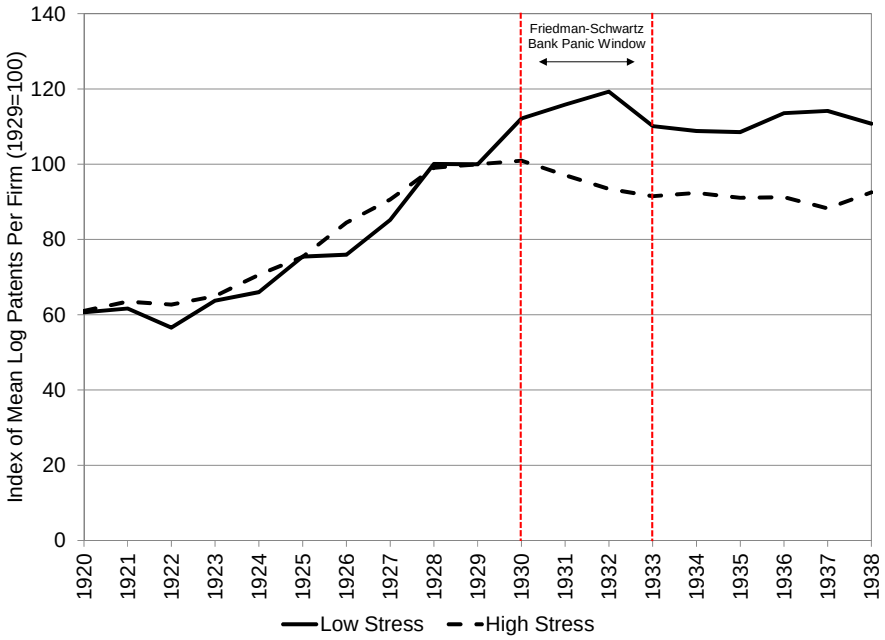
Notes: These figures plots our measure of county-level bank stress against the logarithm of mean patents per firm or citations per patent per firm during the period 1921 to 1929 to determine if firms were sorting into counties. In Figure A β = -0.0024 (t = -0.19) R-sq = 0.001. In Figure B β = -0.004 (t = -0.21) R-sq = 0.001.

Figure 4. Patenting Activity and Bank Stress

A. Publicly Traded and Private Firms



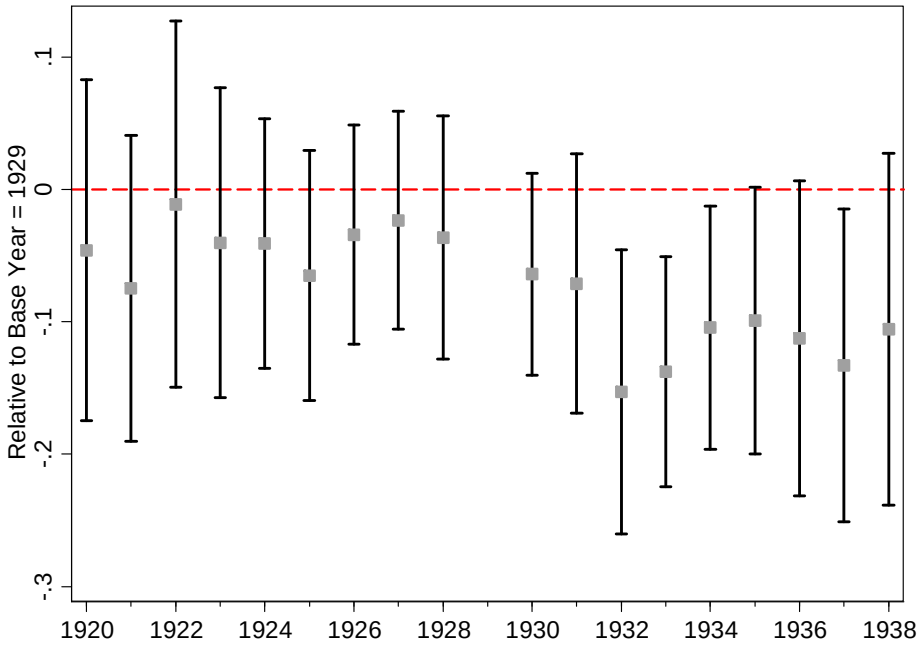
B. Publicly Traded Firms in High and Low Bank Stress Counties



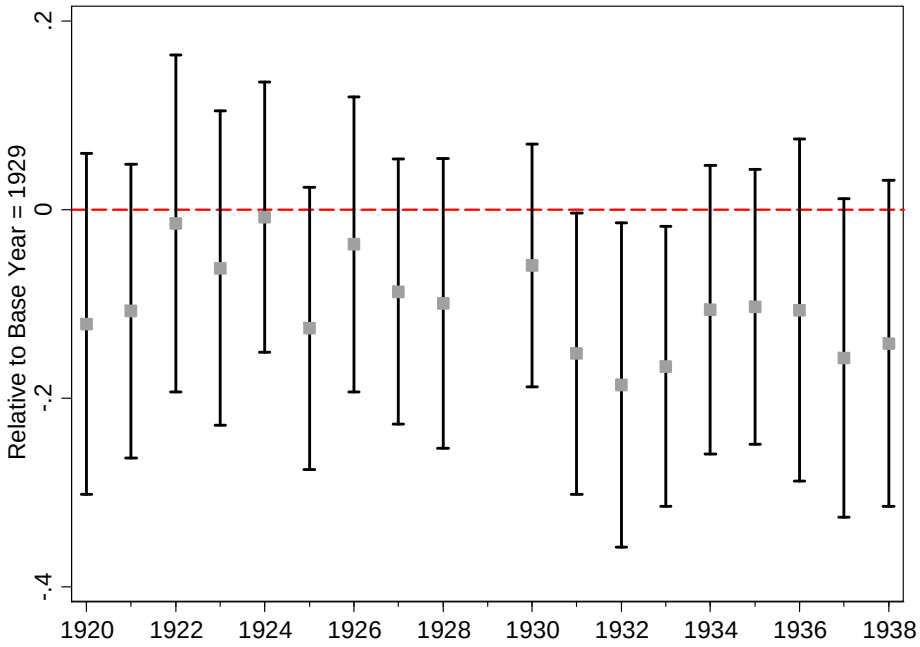
Notes: These figures show patenting activity by the firms in our dataset before, during and after the Friedman Schwartz bank panic window. Figure A compares public and private firms and Figure B publicly traded firms in high stress (i.e. above median) and low stress (i.e. below median) counties.

Figure 5. Time Varying Effects of Bank Stress:
Publicly Traded Firms in High Versus Low Stress Counties

A. Patents to Firms Patenting at Least Once



B. Citations to Firms Patenting at Least Once



Notes: These figures plots time varying effects based on modified specifications of the regressions in Table III.

Table I

Descriptive Statistics

This table reports descriptive statistics based on 2,064 firms from the 1921, 1927, 1931, 1933 and 1938 editions of the National Research Council's *Industrial Research Laboratories of the United States* . We exclude firms if they are not listed in the NRC surveys before the 1931 survey or we do not observe them patenting prior to this point in time. Data on R&D employees comes from the NRC surveys, while data on patenting and patent citations comes from matching each firm in the NRC data to US patent data from the USPTO. Publicly traded firms are identified by matching firms against those listed in the *Commercial and Financial Chronicle* , which tracked stocks traded on any exchange in the United States.

	All firms	Publicly traded firms	Private firms
Number of firms	2,064	261	1,803
Number of firms with patents	1,094	219	889
Total number of patents	142,859	64,556	78,303
Average number of anuual patents per patenting firm	6.9	15.5	4.6
Average number of anuual citations per firm	12.2	46.5	7.2
Average number anuual of citations per patent	1.1	2.1	1.0
Average originality of patent [max of 1]	0.1	0.3	0.1
Average generality of patent [max of 1]	0.1	0.2	0.1
Share of patents in the electricity industry	24%	31%	19%
Share of patents in the chemicals industry	18%	19%	17%
Share of patents in the machinery industry	8%	6%	10%
Share of patents in the automobile industry	8%	12%	4%
Share of patents in the communications industry	8%	8%	8%

Table II
Innovation by Private Firms Relative to Public Firms

This table reports differences-in-differences results of log-transformed firm patents, citations, citations per patent in each firm-year or untransformed originality and generality per patent in each firm-year, regressed on the private firm dummy, the private firm post-period interaction and the fixed effects. Column (1) reports results for all firms in our sample. Columns (2)-(6) restrict the estimations to firms that patented at least once over our sample period. Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

DEPENDENT VARIABLES	Number of patents	Number of patents	Sum of citations to all patents	Citations per patent	Generality of patents	Originality of patents
	(1)	(2)	(3)	(4)	(5)	(6)
Private firm x post	-0.321***	-0.328***	-0.593***	-0.263***	-0.066***	-0.057***
	(0.048)	(0.056)	(0.076)	(0.033)	(0.012)	(0.010)
Private	-0.697***	-0.585***	-0.699***	-0.214***	-0.068***	-0.038***
	(0.075)	(0.077)	(0.096)	(0.038)	(0.014)	(0.010)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	39,216	26,372	26,372	26,372	26,372	26,372
Number of clusters (counties)	348	283	283	283	283	283

Table III
Innovation by Public Firms in More vs. Less Stressed Counties

This table reports differences-in-differences results of log-transformed firm patents, citations, citations per patent in each firm-year or untransformed originality and generality per patent in each firm-year, regressed on the bank stress -post period interaction and the fixed effects. Bank stress is calculated as the zero-one normalized share of 1929 banks that failed between 1930 and 1933. Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

DEPENDENT VARIABLES	Number of patents	Sum of citations to all patents	Citations per patent	Generality of patents	Originality of patents
	(1)	(2)	(3)	(4)	(5)
County-level bank stress x post	-0.072*	-0.065	-0.006	-0.003	-0.008
	(0.042)	(0.056)	(0.025)	(0.009)	(0.008)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	4,503	4,503	4,503	4,503	4,503
Number of clusters (counties)	93	93	93	93	93

Table IV
The Bank Distress and Firm Innovation in More vs. Less Capital Intensive Industries

This table reports differences-in-differences results of log-transformed firm patents, citations, citations per patent in each firm-year or untransformed originality and generality per patent in each firm-year, regressed on the bank stress -post period interaction and the fixed effects. Bank stress is calculated as the zero-one normalized share of 1929 banks that failed between 1930 and 1933. Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

PANEL A: FRIMS IN INDUSTRIES WITH HIGH DEPENDENCE ON EXTERNAL FINANCE (N= 1,444)					
	(1)	(2)	(3)	(4)	(5)
DEPENDENT VARIABLES	Number of patents	Sum of citations to all patents	Citations per patent	Generality of patents	Originality of patents
(a) County-level bank stress x post	-0.207**	-0.258**	-0.089**	-0.039**	-0.037**
	(0.102)	(0.118)	(0.039)	(0.017)	(0.012)
PANEL B: FIRMS IN INDUSTRIES WITH LOW DEPENDENCE ON EXTERNAL FINANCE (N=3059)					
(b) County-level bank stress x post	-0.008	0.023	0.032	0.014	0.006
	(0.042)	(0.066)	(0.031)	(0.011)	(0.010)
PANEL C: WALD TEST FOR THE DIFFERENCE BETWEEN PANEL A AND PANEL B					
Wald test p-value for difference between (a) and (b)	0.074*	0.044**	0.015**	0.006***	0.005***
Year fixed effects	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes

Table V
Instrumental Variable Regressions: The Effect of Bank Distress on Innovation

This table reports results from two-stage least squares regressions where bank stress is instrumented with the concentration of religious activity using data from the 1906 Census of Religious Bodies. Column (1) reports details from the first stage regression. Columns (2) to (7) report the results of IV regressions where the dependent variable is log-transformed firm patents and citations in each firm-year. The fragmentation of religious activity in 1906 is calculated as (1-HHI index), based on the share of the county's population that was affiliated with one of ninety-one different religious denominations in the 1906 Census. A high level on this index is associated with greater religious fragmentation. Bank stress is calculated as the zero-one normalized share of 1929 banks that failed between 1930 and 1933. Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First Stage	IV: Patents			IV: Citations to Patents		
	County-level bank stress x post	Full sample	High dependence	Low dependence	Full sample	High dependence	Low dependence
County-level bank stress x post		-0.200*	-0.659**	-0.004	-0.220	-0.738*	-0.003
		(0.117)	(0.296)	(0.147)	(0.146)	(0.392)	(0.190)
County-level fragmentation of religious activity in 1906 x post	3.947***						
	(1.173)						
Wald test p-value for difference between (High) and (Low)			0.027**			0.036**	
Partial R-squared in first stage	0.095						
F-Statistic in first stage	11.32						
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4,029	4,029	1,292	2,737	4,029	1,292	2,737

Table VI

The Effect of Bank Distress on Firm Innovation in More vs. Less Capital Intensive Industries: Including County-by-Year Fixed Effects

This table reports differences-in-differences results of log-transformed firm patents, citations, citations per patent in each firm-year or untransformed originality and generality per patent in each firm-year, regressed on the bank stress -post period interaction and the fixed effects. Bank stress is calculated as the zero-one normalized share of 1929 banks that failed between 1930 and 1933. Column (1) reports results for all firms in our sample. Columns (2)-(6) restrict the estimations to firms that patented at least once over our sample period. Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

DEPENDENT VARIABLES	Number of patents	Sum of citations to all patents	Citations per patent	Generality of patents	Originality of patents
	(1)	(2)	(3)	(4)	(5)
County level bank stress x post x high dependence	-0.340**	-0.466***	-0.162***	-0.075***	-0.063***
	(0.142)	(0.170)	(0.059)	(0.026)	(0.024)
Bank stress x high dependence	-0.148	-0.205	-0.041	-0.001	0.010
	(0.341)	(0.391)	(0.085)	(0.029)	(0.024)
Post x high dependence	-0.189	-0.207	-0.103	-0.055**	-0.022
	(0.161)	(0.189)	(0.065)	(0.027)	(0.024)
County x Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	4,503	4,503	4,503	4,503	4,503
Number of clusters (counties)	93	93	93	93	93

Table VII
Impact of Bank Distress on R&D Inputs

This table reports differences-in-differences results of the number of research workers and the number of research laboratories, regressed on the bank stress -post period interaction and the fixed effects. Bank stress is calculated as the share of 1929 banks that failed between 1929 and 1933. Since the main effect of bank stress is constant across time, it absorbed in the county-level fixed effects. Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

	Number of research workers	Number of research laboratories
	(1)	(2)
PANEL A: FIRMS IN INDUSTRIES WITH HIGH DEPENDENCE ON EXTERNAL FINANCE (N=220)		
(a) Bank stress × post	-0.498**	-0.121
	(0.242)	(0.078)
PANEL B: FIRMS IN INDUSTRIES WITH LOW DEPENDENCE ON EXTERNAL FINANCE (N=568)		
(b) Bank stress × post	-0.109	-0.057
	(0.116)	(0.043)
PANEL C: WALD TEST FOR THE DIFFERENCE BETWEEN PANEL A AND PANEL B		
Wald test p-value for difference between (a) and (b)	0.115	0.420
Year fixed effects	Yes	Yes
County fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes

Appendix Table I

Estimating R&D Firms' share of Bank Lending

This table estimates the share of total bank lending in each year accounted for by NRC firms. Column 2 provides data on aggregate real bank lending in the United States, taken from *Banking and Monetary Statistics* (Number 18, All Member Banks, Principal Assets and Liabilities on Call Dates 1914-1941). Column 3 reports the number of publicly traded NRC firms in the data in each year and column 4 reports the average value of bank debt on the balance sheet of firms for which data is available, as reported in the *Moody's Manual of Industrials* . Column 5 creates aggregate measures of bank borrowing by publicly traded NRC firms, using the estimates of individual firm-borrrowing and the total number of R&D firms. Finally column 6 provides estimates of the share of total bank lending that is due to NRC firms. Column 6 highlights that while there may be individual cases of an R&D firm accounting for a large share of bank lending, in general, the borrowing by NRC firms will have been small compared to the overall lending by banks.

Year	Aggregate real bank lending in the US ($M)	Number of publicly traded NRC firms	Average bank debt for NRC firms with available data ($M)	Bank lending by NRC firms in aggregate [3]x[4]	NRC firms' share of aggregate bank lending [5]÷[2]x100
[1]	[2]	[3]	[4]	[5]	[6]
1921	17,437	57	7.147	407	2.3%
1927	23,361	122	5.041	615	2.6%
1931	24,606	177	2.899	513	2.1%
1933	16,902	186	2.775	516	3.1%
1938	15,690	234	2.158	505	3.2%

Appendix Table II

Impact of Bank Distress on Public-Firm Finances

This table reports differences-in-differences results of log-transformed firm balance sheet variables in each firm-year, regressed on the bank stress -post period interaction and the fixed effects. Bank stress is calculated as the zero-one normalized share of 1929 banks that failed between 1930 and 1933. Observations based on publicly traded firms for which balance sheet data are available in *Moody's Manual of industrials* . Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

DEPENDENT VARIABLES	Notes payable and bank debt	Cash
	(1)	(3)
Bank stress × post	-0.039**	-0.080**
	(0.019)	(0.039)
Year fixed effects	Yes	Yes
County fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Number of observations	1,982	1,982
Number of clusters (counties)	75	75

Appendix Table III

Industries More vs. Less Dependent on External Finance

This table reports the concordance we establish between the NRC firms in our sample and the Rajan and Zingales (1998) measure of external finance. Given that we are looking at publicly traded firms for the analyses that are split by industry, we focus on the RZ measure of external finance for mature companies. In instances where we have a unquie ISIC mapping, we use the measure calculated by RZ in Table I of their paper. In instances where we have multiple SIC codes mapped, we use the average of their measures. We classify industries as having above median dependence on external finance if the measure reported in column (2) is greater than 0.12. Our robustness check, reported in Appendix Table IV, classifies an industry as having above median dependence on external finance if the measure in column (3) is above 0.06

Industry	Mapping to ISIC Code used in RZ 1998 Paper	RZ Measure of Mature Company Dependence on External Finance	Bank Loans Payable / Fixed Assets for firms in our sample
	(1)	(2)	(3)
Rubber and Plastics	355, 356	-0.12	0.06
Food and Kindred	311, 313	-0.10	0.06
Miscellaneous	390	-0.05	0.05
Chemicals	3511, 352	-0.05	0.05
Stone, Clay and Glass	362	0.03	0.18
Metals	371, 381	0.07	0.06
Petroleum and Coal	353, 354	0.07	0.03
Paper and Products	341	0.10	0.04
Automobiles and Transportation	3843, 384	0.14	0.09
Textile Mill Products	321	0.14	0.32
Mineral Products	369	0.15	0.08
Instruments	385	0.19	0.03
Medical Equipment	385	0.19	-
Machinery	382	0.22	0.23
Electrical Equipment	383	0.23	0.07
Communications	3832	0.39	0.10

Appendix Table IV

The Bank Distress and Firm Innovation in More vs. Less Capital Intensive Industries

This table reports differences-in-differences results of log-transformed firm patents, citations, citations per patent in each firm-year or untransformed originality and generality per patent in each firm-year, regressed on the bank stress -post period interaction and the fixed effects. Bank stress is calculated as the zero-one normalized share of 1929 banks that failed between 1930 and 1933. Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

PANEL A: FRIMS IN INDUSTRIES WITH HIGH DEPENDENCE ON EXTERNAL FINANCE (N= 1,501)					
	(1)	(2)	(3)	(4)	(5)
DEPENDENT VARIABLES	Number of patents	Sum of citations to all patents	Citations per patent	Generality of patents	Originality of patents
(a) County-level bank stress x post	-0.181**	-0.196**	-0.055	-0.031*	-0.031**
	(0.086)	(0.095)	(0.034)	(0.017)	(0.013)
PANEL B: FIRMS IN INDUSTRIES WITH LOW DEPENDENCE ON EXTERNAL FINANCE (N=3002)					
(b) County-level bank stress x post	-0.018	-0.006	0.017	0.011	0.003
	(0.046)	(0.070)	(0.033)	(0.012)	(0.010)
PANEL C: WALD TEST FOR THE DIFFERENCE BETWEEN PANEL A AND PANEL B					
Wald test p-value for difference between (a) and (b)	0.087*	0.104	0.126	0.031**	0.031**
Year fixed effects	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes

Appendix Table V
Trajectory of Innovation Controlling for Changes in Inputs

This table reports differences-in-differences results of log-transformed citations per patent in each firm-year or untransformed originality and generality per patent in each firm-year, regressed on the bank stress -post period interaction, measures of the number of research workers, research labs and the fixed effects. Bank stress is calculated as the zero-one normalized share of 1929 banks that failed between 1930 and 1933. Standard errors are clustered at the county-level. Significance is at the * 10, ** 5 and *** 1 percent levels, respectively.

		(1)	(2)	(3)
	DEPENDENT VARIABLES	Citations per patent	Generality of patents	Originality of patents
	PANEL A: FRIMS IN INDUSTRIES WITH HIGH DEPENDENCE ON EXTERNAL FINANCE (N= 1,444)			
(a)	County-level bank stress x post	-0.081**	-0.037**	-0.035***
		(0.038)	(0.018)	(0.012)
	Log number of research workers	0.060*	0.016	0.013*
		(0.030)	(0.011)	(0.007)
	Log number of research laboratories	0.075	0.031	0.026
		(0.064)	(0.023)	(0.023)
	PANEL B: FIRMS IN INDUSTRIES WITH LOW DEPENDENCE ON EXTERNAL FINANCE (N=3059)			
(b)	County-level bank stress x post	0.034	0.015	0.007
		(0.033)	(0.012)	(0.010)
	Log number of research workers	0.087***	0.036***	0.023***
		(0.026)	(0.009)	(0.007)
	Log number of research laboratories	0.089	0.008	0.007
		(0.070)	(0.021)	(0.019)
	PANEL C: WALD TEST FOR THE DIFFERENCE BETWEEN PANEL A AND PANEL B			
	Wald test p-value for difference between (a) and (b)	0.015**	0.005***	0.004***
	Year fixed effects	Yes	Yes	Yes
	County fixed effects	Yes	Yes	Yes
	Industry fixed effects	Yes	Yes	Yes