The Real Effects of Hurting Lending Relationships: Evidence From Banking Deregulation and Innovation*

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Abstract

We examine the effect of lending relationships on innovative activities. Using banking deregulation as a shock to lending relationships, we find that when relationships are hurt: i) the number of innovators decreases; ii) firms reallocate their projects away from R&D investment and toward investment in physical assets; iii) the share of technologically innovative industries in total value added declines. These findings and others are consistent with the hypothesis that evaluating innovative projects requires soft information produced by close relationships between lenders and borrowers. Overall, our results support the idea that the banking structure shapes comparative advantages.

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1 Introduction

Does banking structure shape comparative advantages? The banking literature shows that banking market characteristics such as the degree of competition and banks' size determine the nature of relationships between banks and borrowers and thus the type of information they can exchange. While banks acquire subjective and abstract ("soft") information when they have strong relationships with debtors, they instead use standardized and verifiable ("hard") information when they remain at arm's length. The nature of information on which banks rely is important as it conditions the type of projects that they are able to evaluate and thus to finance. In other words, the banking market structure can shape the specialization of the economy.

We examine this view in the context of innovation. Innovative projects involve investments in intangible assets and human capital which are difficult to evaluate by external lenders. Innovation also tends to occur in new areas of economic activity in which the potential of a project can hardly be assessed by comparison with similar projects. In addition, a number of innovative projects are undertaken by young start-ups with little easily verifiable track record. These characteristics imply that innovative projects suffer from potentially severe information problems. In addition, R&D investments generally have little collateral value, which therefore cannot be used to mitigate credit constraint produced by these information problems. Lending relationships alleviate these problems by allowing banks to acquire soft information about projects such as the competence and trustworthiness of the management, as well as the types of investment opportunities that could arise. Therefore, we expect banking markets characterized by strong lending relationships to have a comparative advantage in the financing of innovation.

We test this hypothesis using the wave of banking deregulation passed in different

U.S. states from the early 1970s to the mid-1990s. By removing restrictions on bank expansion within state borders, intrastate deregulation has intensified banking competition and increased banks' size. Theory suggests that such deregulation hurts lending relationships and induces banks to rely more on hard information, as competition is an impediment to the creation of lending relationships (Petersen and Rajan, 1995) and large banks have difficulties to deal with non-verifiable soft information that cannot be easily passed along within the hierarchy (Stein, 2002). The staggered timing of deregulation across states permits a difference-in-difference identification strategy to assess a causal effect of hurting lending relationships. We have three sets of findings.

Our first set of empirical evidence shows that deregulation impedes innovation by hurting lending relationships. We measure innovation by the number of firms which file at least one patent at the U.S. Patent and Trademark Office (USPTO). An appealing feature of USPTO data is that they cover the whole universe of patents – filed by both public and private firms. Figure 1 shows a preview of our results. It plots the number of innovators around deregulation relative to a control group of states which do not deregulate. The number of innovators starts to decline three years after deregulation and ends up 20% below its initial level after ten years. Consistent with the idea that this negative effect is due to a restriction in bank lending, the effect materializes only in industries with high dependence on external finance and in industries with little collateral. The negative effect on innovation is also stronger for younger firms and for firms operating in younger industries. This finding is in line with the notion that hurting lending relationships impedes the production of soft information, which is crucial to evaluate projects in young firms and in young industries.

[INSERT FIGURE 1 ABOUT HERE]

To test more directly the soft information story, we classify industries by the nature of information: hard versus soft. We define three measures of dependence on soft information. Our first proxy is the distance between banks and borrowing firms, where a small distance is indicative of relationship lending and reliance on soft information, while a long distance is indicative of arm-length lending and reliance on hard information. Our second proxy is borrowed from Landier, Nair and Wulf (2009) and is defined as the change in distance between banks and borrowers over time. The idea is that the increase in distance is due to innovations in information technology which are more widely implemented in industries where information can be more easily hardened (Petersen and Rajan, 2002). The last measure is the length of relationships between banks and firms, with longer relationships being indicative of stronger reliance on soft information. For all three proxies, we find that the decline in innovation is stronger in industries where soft information is more prevalent.

Our second set of findings focuses on the allocation of investment projects *within* firms. First, we find a decrease in the quality of innovation as well as in the risks taken by innovators, measured by the average number of patent citations and the standard deviation of the number of citations respectively. Therefore, when relationships are hurt, innovators focus on more incremental, less risky innovations. Second, we focus on public firms and compare the evolution of investment in R&D and investment in physical capital. Consistent with the notion that information is softer in R&D projects, we observe a reallocation of investments away from R&D and toward physical assets.

In the third part of the paper, we show that our micro-level effects add up to macroeconomic effects. We find that states experience a decrease in the share of the most innovative industries in their GDP after they deregulate. Moving from complete regulation to complete deregulation reduces the weight of high-tech industries by about 14%. In other words, deregulation reshapes their specialization toward less innovative sectors. We conclude therefore that relationship-based financing matters not only when institutions are underdeveloped (Rajan and Zingales, 1998b) but also when financial markets are well developed such as in the U.S., when it comes to innovation.

Our paper contributes to the literature on the real effects of lending relationships.[1] The literature argues that relationships alleviate credit constraints for informationally "difficult" debtors. For instance, Petersen and Rajan (1994) find that relationships ease credit availability for young firms while Berger and Udell (1995) point our that they reduce collateral requirement. Hellmann, Lindsey and Puri (2008) show that the perspective to build relationships motivates banks to fund VC backed firms. The literature also stresses the comparative advantage that small and local banks have at collecting soft information, while big and foreign banks interact more impersonally and are quite willing to give out arm's length or "transaction" loans based on hard information (Berger et al. 2005, Mian, 2006, Liberti and Mian, 2009, Hertzberg, Liberti and Paravisini, 2010). Overall, these results suggest that banking deregulation, by hurting relationships, can have adverse effects on the real economy. Indeed, Zarutskie (2006) finds that young firms raise less bank debt and invest less after banking deregulation, while Detragiache, Tressel and Gupta (2008) show that private credit is lower in low income countries with larger foreign bank penetration.

We relate more generally to the vast literature on the real effects of banking reforms. More specifically, Black and Strahan (2002), Cetorelli and Strahan (2006), Bertrand, Thesmar and Schoar (2007), Kerr and Nanda (2009), Levine, Levkov and Rubinstein (2011) find that deregulation fosters entry. While our results may seem at odds with these papers, they actually suggest that more entry does not necessarily imply more

[1] Ongena and Smith (2000) provide a broad survey of the relationship banking literature.

innovation. This is consistent with Hurst and Pugsley (2011) who show that most new firms are not dynamic innovative start-ups.

Finally, our paper relates to the literature on the link between financial environment and innovation. Laeven, Levine and Michalopoulos (2012) identifies the screening ability of the financial system as a crucial determinant of innovation. Brown, Fazzari and Petersen (2009) and Brown, Martinsson and Petersen (2012) demonstrate that equity market development matters for innovation, because equity is well-suited to the financing of intangible projects plagued by information problems.[2] We show that the structure of the banking market also matters by determining the nature of information produced: banking markets characterized by relationship lending produce soft information which facilitates the financing of innovation. We thereby add to the literature stressing the importance of debt financing for innovation. Robb and Robinson (2011) report that debt accounts for a significant part of the financing of US medium-sized innovative firms. Accordingly, innovation is fostered by banking market development (Benfratello, Schiantarelli and Sembenelli, 2008), debtor friendly bankruptcy codes (Acharya and Subramanian, 2009), and bank diversification (Amore, Schneider and Zaldokas, 2012).[3]

The rest of the paper is organized as follows. Section 2 describes the data and the empirical strategy. Section 3 presents the results. Section 4 concludes.

[2] The role of other dimensions of equity financing have been investigated, such as institutional ownership (Aghion, Van Reenen and Zingales, 2009) and antitakeover laws (Atanassov, 2012).

[3] Other related work includes Cornaggia, Tian and Wolfe (2012) who show that credit availability affects the dynamic of public firms' acquisitions of small innovative targets, and Chava et al. (2012) who argue that an increase in banks' bargaining power vis-a-vis borrowers impedes innovation.

2 Data and Empirical Strategy

2.1 Banking deregulation and its consequences for relationships

Before the 1970s, most U.S. states had strong banking market regulations. Branching was either prohibited or strongly limited, with the exception of 12 states which started to deregulate in the 1960s. Starting in 1970 however, all the other states progressively deregulated their restrictions within their borders. States generally relaxed restrictions on within-state expansion in three steps: by permitting the formation of multibank holding companies, by permitting branching by means of merger and acquisition (M&A) only, and by permitting unrestricted (de novo) branching, thereby allowing banks to enter new markets by opening new branches. Figure 2 illustrates the timing of the deregulation for the three dimensions. Because we do not have priors about which of these three steps should have the greatest impact, we follow Black and Strahan (2001) and construct a deregulation index, which equals 0 if a state permits neither branching via M&A, nor de novo branching, nor the formation of multibank holding companies; otherwise, the index equals the sum of the number of ways banks may expand within state.

[INSERT FIGURE 2 ABOUT HERE]

The deregulation has changed the local banking market structure along two dimensions that hurt lending relationships and induce banks to rely more on hard information.

First, the deregulation creates a more competitive environment by allowing banks to enter new markets and threaten incumbent banks.[4] Theory suggests that poorly competitive banking markets are a fertile ground to build lending relationships as borrowers have few opportunities to switch to another bank. Petersen and Rajan (1994) argue that,

[4]See, e.g., Stiroh and Strahan (2003) for evidence that deregulation has effectively intensified bank competition.

when banks are protected from competition, they have more incentives to collect soft information about borrowers as they are better able to reap the rewards of their investment in the future. Indeed, upon observing that a relationship loan has been granted to the firm, rival banks would infer that the firm has valuable projects and compete away the informational rent of the bank which initially acquired soft information. In other words, once soft information has been used, it becomes hard information for rival banks. Therefore, bank competition impedes relationship lending.

Second, relaxation surrounding bank expansion led to an increase in average bank size through internally generated growth (for example, de novo branching) and through branch and bank purchases, resulting in local lending markets dominated by bigger banks.[5] A number of theories suggest that soft information is difficult to share across organizational layers. The precise channels vary from ex-ante incentives for information collection (Aghion and Tirole, 1997; Stein, 2002), to strategic manipulation of information (Crawford and Sobel, 1982) and ex-post communication costs (Bolton and Dewatripont, 1994). Regardless of the underlying channels, these theories predict that large banks have a comparative disadvantage at using soft information. Therefore, the intrastate deregulation has produced a lending market dominated by large banks evolving in a more competitive environment, where banks have rationally preferred to rely on hard information.

Note that in this paper, we focus on *intrastate* deregulation and do not consider the waves of *interstate* banking and branching deregulation that took place during the 1980s and 1990s. During the 1980s many states entered into reciprocal arrangements with other states whereby their banks could be bought by banks from other states. Then, restrictions to interstate branching were lifted following the 1994 passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act.[6] In this paper, we do not consider these two

[5]See, e.g., Table 5 in Jayaratne and Strahan (1998).

[6]See Kroszner and Strahan (2011) for a detailed history of banking regulation and deregulation.

waves of *interstate* deregulation because they have potentially two effects that we cannot disentangle. Interstate deregulation hurts lending relationships but also permits banks to diversify risks across states.[7] Better diversification of state idiosyncratic risk may allow banks to make more risky loans, which could foster innovation. By contrast, diversification benefits are much lower with within-state expansion. Therefore, intrastate deregulation is a more appropriate natural experiment to isolate the effect of lending relationships.

2.2 Measure of innovation

We use patents filed with the U.S. Patent and Trademark Office (USPTO) compiled in the National Bureau of Economic Research (NBER) Patents File (Hall, Jaffe, and Trajtenberg, 2001). The data contain all patents granted in the U.S. along with information about the patentee (unique identifier, institutional characteristics, nationality, geographic localization) and about the patent (year of application, technology class, number of citations received).

An appealing feature of the NBER Patents File is that it covers the whole universe of patents filed in the U.S., which implies that it is free of any selection bias. In particular, it allows to assess the effect of banking deregulation on the whole innovative capacities – including both public firms present in Compustat as well as young and private firms. This feature of the data is important as it will allow us to rule out explanations of our results based on a change in the share of innovation conducted by public vs. private firms and really estimate the total amount of innovation produced by each state. It is also important to have private firms in the data, because those firms are likely to be affected by changes in local bank markets since they have less access to national capital markets.

[7] See Amore, Schneider and Zaldokas (2012) who instrument bank diversification with interstate deregulation.

While the NBER patent data do not have standard industry classification such as SIC, they have a classification based on the technology of patents. We use the two-digit classification which counts 37 technology classes listed in Table 1, Panel A.[8] With a slight abuse of terminology we will use the terms "technology class" and "industry" interchangeably.

We only keep patents filed by U.S. corporations, therefore excluding foreigners as well as universities and governmental agencies. We date our patents according to the year in which they were applied for. This avoids anomalies that may be created due to lag between the date of application and the granting date. We consider all patents filed between 1968 (i.e., two years before the beginning of the deregulation period) and 1998 (i.e., four years after the end of the deregulation period). To measure the extensive margin of innovation, we count the number of uniquely identified firms which file at least one patent (hereafter "innovators") at the state-year-industry level.[9] To assess the effect on the intensive margin of innovation, we compute the average and median number of patents by innovator at the state-year-industry level. We proxy for the quality of innovation with the average and median number of citations received by patents at the state-year-industry level. We also measure the riskiness of innovations by the standard deviation of the number of citations. Finally, we follow the banking deregulation literature and exclude Delaware. This leaves us with a balanced panel of 37 industries in 50 states over 31 years.

[8] We have re-run all our regressions and obtained similar results with the finest three-digit classification which counts 422 technology classes.

[9] When an innovator files patents in several industries in a given state and year, we assign the innovator to the industry(ies) in which it filed the largest number of patents (if the maximum is reached for several industries). This assumption is consistent with interpreting the number of innovators as a measure of the extensive margin of innovation, as it avoids double counting.

In 2% of cases the same innovator files patents in two different states and in 0.5% of cases in more than two states. This occurs when a firm has labs in several states as patents are located in the same state as the lab to which the patent is associated. In this situation, we count the firm as one innovator in all the states in which it files patents. We have re-run all our regressions and found identical results when we assign the firm to the first state in which it appears in the data, and when we assign the firm to the state in which it files the largest number of patents.

Panels A and B of Table 1 report summary statistics for the different variables used as well as the number of innovators for each of the 37 industries. There is an average (median) of 5.6 (1) innovators in a given state-year-industry cell with a substantial heterogeneity across both industries and states. An innovator files an average (median) of 4 (1) patents and a patent is cited by an average (median) of 11 (6) subsequent patents.

[INSERT TABLE 1 ABOUT HERE]

Although patents have long been used as an indicator of innovative activity (Griliches, 1990), this measure has its drawbacks. Not all firms patent their innovations, because some inventions do not meet the patentability criteria and because the inventor might rely on secrecy or other means to protect its innovation. In addition, patents measure only successful innovations. We partially address this concern in Section 3.2.2 by using R&D expenses as an alternative proxy for innovation.

2.3 Identification strategy

We explain the identification strategy in the case of our baseline regression which focuses on the effect of deregulation on the number of innovators (all the other regressions rely on the same identification strategy). Following the innovation literature, we estimate a Poisson model to take into account the counting nature of the dependent variable:[10]

$$E\left[Innovators_{jst}\right] = \exp\left(\alpha_j + \gamma_s + \delta_t + \beta \ Deregulation_{st} + X_{st}\right), \qquad (1)$$

where industries are indexed by j, states by s, and years by t. The Poisson model is estimated by maximum likelihood and standard errors are clustered at the state level to account for serial correlation and correlation within states.

[10]See Hausman, Hall, and Griliches (1984) for a discussion of count data models.

The parameter of interest is β. It measures the incremental effect of one step of deregulation (out of three possible steps) on the number of innovators. Industry fixed effects account for the heterogeneity of the propensity to innovate and to patent innovation across industries. State fixed effects capture time-invariant determinants of innovation in the different U.S. states, such as the size of the state, the sectorial composition and the level of education. Year fixed effects control for aggregate shocks and common trends in innovation activity. The identification of β therefore relies on comparing the number of innovators before and after deregulation relative to a control group of states not experiencing a change in regulation.

However it could well be that other factors that are time-varying at the state level affect the propensity to innovate. If these factors vary precisely at the time of the deregulation, it could produce spurious correlations. To mitigate this problem, we add time-varying control variables at the state level: the annual number of college degrees granted, the annual number of doctorates granted, the annual amount of federal funds for research and development, and the volume of capital invested each year by venture capitalists.[11] However, these control variables can potentially bias our results as they are likely to be endogenous (Roberts and Whited, 2011). For instance, there is some evidence that VC activity is driven by demand (Gompers and Lerner, 1998). If this is the case then, adding VC activity as a control variable biases the estimated effect of deregulation toward zero. The same argument can be made for the level of education. Similarly, federal R&D expenses may be endogenous if they are directed toward states which lag behind in terms of innovation or, on the contrary, toward states which experience innovation booms. Therefore, adding the control variables may or may not produce a bias in the estimation of β. For this reason, we report all the results both with and without these controls.

[11]Data on educational attainment and federal R&D expenses come from the NSF CASPAR database, and information on VC funds is from Venture Xpert.

Figure 1 gives a preview of our main result. It plots the evolution of the number of innovators during the time window from ten years before to ten years after the year in which the state allows branching through M&A. It shows clearly that the number of innovators decreases after deregulation. Reassuringly, there is no discernable pattern before the deregulation date. In particular, the number of innovators ten years before deregulation is almost equal to the number of innovators at the time of deregulation. This is consistent with our identifying assumption that deregulation is not endogenous to innovation activity or to other economic variables related to innovation.[12] Instead, the graphical analysis suggests that the deregulation shock *causes* a decrease in innovation activity. We run formal statistical tests in the following section.

3 Results

3.1 Impact on the number of innovators

3.1.1 Baseline results

We start by investigating the effect of banking deregulation on the number of innovators. Results are reported in Table 2. Column (1) shows that every deregulation step leads to a statistically significant decline in the number of innovators by 9.7%. In columns (2) to (4) we add time-varying control variables for the level of education, federal R&D spending, and VC activity at the state-level. All these variables are significant with the expected sign except federal R&D spending which is insignificant, which may be explained by the fact that federal spending is directed toward moderately innovative states. The coefficient on the deregulation index remains negative at -7.1% and significant at the 5%

[12] Kroszner and Strahan (1999) document that deregulation occurs earlier in states with fewer small banks and in states with more small firms. Figure 1 suggests that these characteristics are not correlated with trends in innovation activity.

level. Given that the deregulation index ranges from 0 to 3, it means that the number of innovators drops by a little more than 20% when a state moves from being fully regulated to being fully deregulated. In the following, we report all our regressions both with and without the control variables. Given that both sets of results are very similar, we will only comment the results obtained when controls are included to keep the exposition concise.

[INSERT TABLE 2 ABOUT HERE]

In columns (5) and (6) we exploit more fully the time dimension of the panel to check that we are not capturing a trend. We decompose each of the three components of the deregulation index into four dummy variables associated which four periods around the deregulation date: more than 4 years before deregulation, the 4 years preceding deregulation, the 4 years following deregulation, and more than 4 years after deregulation. Then, we sum over the three components of the deregulation index to obtain four dummy variables corresponding to the four time periods around each step of deregulation. The deregulation year is the reference year.

First, as seen in Figure 1, there is no pre-deregulation trend. Second, it takes some time before the effects of deregulation materialize. When we include the control variables, the number of innovators decreases by 2.7% in the first four years after deregulation while it decreases by 9% after that. This delay is consistent with the hypothesis that it is through an increase in competition and in bank size that banking deregulation impedes innovation. For instance, Jayaratne and Strahan (1998) show that it takes a couple of years before deregulation has an impact on the banking market. In addition, we also expect a delay between the time an innovative project is funded and the moment when the firm will file the patent application.

3.1.2 Is the effect stronger for credit constrained firms?

If the effect on the number of innovators comes from a change in lending conditions, industries that rely more on external finance to cover their financial needs should be more affected. We follow the methodology of Rajan and Zingales (1998a) to investigate this hypothesis and calculate the degree of external financial dependence as the average fraction of investment which cannot be financed by current cash flows at the three-digit SIC industry level. We then map this variable into the 37 patent classes that we use in our regressions, and we split this measure into three terciles.[13] Finally, we run the regression on the deregulation index interacted with the terciles of financial dependence to assess in which tercile deregulation has the strongest effect.

In this regression it is necessary to also interact the state and year fixed effects with the terciles of financial dependence, else the coefficients on the deregulation index interacted with financial dependence can be biased. Suppose indeed that we do not interact the year fixed effects with financial dependence. Since states deregulate but never re-regulate, the deregulation index trends upward on average across states and industries. This implies that, if financially dependent industries have different trends in innovation activity, then the interaction term of deregulation and financial dependence will pick up this spurious correlation. Year fixed effects interacted with financial dependence permit to control for such potential confounding effects. State fixed effects must be interacted with financial dependence for a similar reason. Assume they are not, and that states with higher values of the deregulation index on average over the sample period, have different intensity of innovation across the three terciles of financial dependence, then again the interaction term of deregulation and financial dependence will be biased. State fixed effects interacted with

[13] The exact mapping procedure is described in Appendix A.1 and is a method similar to Acharya and Subramanian (2009).

financial dependence solve this potential omitted variable problem. For similar reasons, when the state-time varying controls are included in the regression, they must also be interacted with financial dependence. To simplify the tables however, we do not report the coefficients of the controls or their interactions with the terciles of financial dependence.

Another source of cross-sectional variation is the amount of collateral. Firms with more tangible assets should be able to borrow even when banking relationships deteriorate, as they can always pledge their collateral to get a loan.[14] Therefore, we expect the impact of banking deregulation to be lower in industries which use less tangible assets. Similar to the methodology for the degree of dependence toward external finance, we measure the collateral value as the ratio of net property, plant and equipment over total assets in Compustat, map three-digit SIC industries into patent classes, and decompose into terciles that we interact with the deregulation index, the year and state fixed effects, and the controls.

[INSERT TABLE 3 ABOUT HERE]

Results are reported in Table 3. Columns (1) and (2) show that the negative effect of banking deregulation is monotonic in the degree to which industries rely on external finance. The difference between the top tercile and the bottom tercile (the reference group) of financial dependence is -11% significant at the 5% level when controls are included. Industries in the bottom tercile of financial dependence experience no significant change in the number of innovators after the deregulation. These results are consistent with the hypothesis that banking relationships matter for innovation, as industries which do not need them are not affected by a weakening of these relationships.

[14] For instance, Chaney, Sraer and Thesmar (2011) show that collateral helps alleviate credit constraints. In the context of lending relationships, Berger and Udell (1995) find that banks ask less collateral when they maintain strong relationships with the borrowing firm.

Columns (3) and (4) show similar results when industries are ranked by collateral value. While industries with high collateral are not affected at all, the difference between the bottom tercile and the top tercile of collateral intensity is -12% and significant at the 1% level. Therefore, collateral helps mitigate the weakening of banking relationships.

3.1.3 The effect of age

Another prediction is that firms which do not have much of a track record should suffer more from a weakening of banking relationships (see, e.g., Petersen and Rajan, 1994). To test this prediction, we consider two dimensions of age: the age of the innovator itself and the age of the industry in which it operates. Young firms rely more on relationship lending because they need to share soft information with lenders who, if they remained at arm's length, would have little information about the competence and trustworthiness of the management, as well as the kinds of investment opportunities that could arise. We also expect the age of the industry to matter even after controlling for firm age. Regardless of the firm's ability to produce hard information about itself (such as financial statements), its projects remain hard to evaluate if it operates in a young industry and the banker remains at arm's length. Indeed, it is more difficult to assess the quality of a project when there is no similar product already on the market than when several firms have already successfully commercialized similar innovations. Therefore the ageing of an industry produces hard information for all the projects in the industry. In other words, it was probably more difficult to assess the quality of a project in the computer sector before the emergence of Microsoft, Sun Microsystems and Apple than after.

Innovator age is calculated as the number of years since the innovator first filed a patent application. We identify young innovators as those whose age is less than or equal to 3 years (the median innovator age) and old innovators as those whose age is above.[15] Industry age is defined as the median age of innovators in the industry. We adopt the same threshold of 3 years (also the median industry age) to classify an industry as young or old.

To investigate the effect of age, we count the number of young innovators and the number of old innovators at the state-year-industry level. We therefore obtain a four-dimensional balanced panel where the new dimension is the age category of innovators: young or old. We construct a dummy variable equal to one in the young innovator age category, as well as dummy variable equal to one if the industry is classified as young. We then regress the number of innovators at the state-year-industry-innovator age category level on the two age dummies, their interactions with deregulation, and the same set of fixed effects and controls as in previous regressions.[16] It should be noted that once data are aggregated by industry and innovator age category, the two age dummies are not correlated since each state-year-industry has two age innovator categories (one young, one old), no matter the age of the industry. This implies that running separate regressions or including both age dummies in the same regression yield similar estimates.

[INSERT TABLE 4 ABOUT HERE]

Results are reported in Table 4. In columns (1) and (2) we consider the effect of innovator age and find that deregulation essentially affects young innovators. While the effect on old innovators (the reference group) is negative and insignificant, the number of young innovators decreases significatively by 5.1% compared to old innovators. In columns (3) and (4) we consider industry age and find that compared to old industries,

[15]The NBER Patents File starts in 1965 but coverage is good only starting in 1968 which creates a truncation problem in the definition of age. To limit this problem, we start the sample period in 1970 when studying the effect to age.

[16]For the same reasons explained in Section 3.1.2 we also interact year and state fixed effects and controls with the age dummies.

the number of innovators in young industries decreases by 7.5%. As explained above, results are identical when we include both variables in columns (5) and (6). The results are consistent with the hypothesis that hurting lending relationships is more harmful to firms and industries with little track record.

3.1.4 Testing more directly the effect of soft information

To test more directly the hypothesis that innovation declines because lending relationships are hurt, we identify industries where soft information is more prevalent and assess whether these industries are more affected by deregulation. To do so, we use the National Survey of Small Business Firms (1987 and 1998), which contains a thorough documentation of firms' relationship with financial institutions.[17] We create three measures of industry-level reliance on soft information.[18] The first one is the average distance between firms and their main lenders in 1987 (the first year the survey was conducted) at the two-digit SIC level. As shown by Petersen and Rajan (2002), the distance between bank lending office and the borrowing firm is greater in hard information industries as the communication does not require personal interactions. The second proxy based on Landier, Nair and Wulf (2009) is the average distance increase between 1987 and 1998. The idea is that, in hard information industries the distance between banks and borrowers increases as lenders take advantage of technological developments. Indeed, the average distance has increased over time and much more in some industries than in others, which allows us identify hard information industries. The last proxy is the average length of the relationship between banks and borrowers in 1987 (Petersen and Rajan, 1994). Longer relationships are indicative of stronger reliance on soft information. The correlations between these three measures are low or even negative. The correlation between (minus)

[17]For more details about this database, see Petersen and Rajan (2002).

[18]We describe in more details how we construct these variables in Appendix A.2.

distance and (minus) change in distance is −0.42, between (minus) distance and length of relationship is −0.01, and between (minus) change in distance and length of relationship is 0.23. These low correlations suggest that we are capturing different dimensions of soft information. As before, we map these three variables which are defined at the two-digit SIC level with the patent industry classification, and we split them into three terciles.

[INSERT TABLE 5 ABOUT HERE]

We test whether the effect of deregulation is stronger in soft information industries. Results are reported in Table 5. With all three measures, the negative effect of deregulation is stronger in the tercile of industries which rely most on soft information. The difference between the top tercile and the bottom tercile of soft information intensity is −5.2% when nature of information is proxied by average distance with lender, −3.8% when information is proxied by change in distance, and −11% when using the length of relationships. All these coefficients are statistically significant. These results give a consistent story about why banking deregulation affects innovation. The shock it creates on lending relationships tightens credit rationing for firms which have to communicate through soft information and therefore reduces their ability to innovate.

3.2 Impact on project types

3.2.1 The choice of innovative projects

We now explore how deregulation affects innovation at the intensive margin. More specifically, we consider three dimensions of the intensive margin: the quantity of innovation, the quality of innovation, and the riskiness of innovation. We measure the quantity of innovation by the average (or median) number of patents filed by each innovator. To proxy for quality, we use the average (or median) number of citations received by patents, which is a standard measure of patent quality (e.g., Hall, Jaffe, and Trajtenberg, 2005). Finally, to evaluate the riskiness of innovative projects, we compute the standard deviation of the number of citations received by patents. We run standard OLS regressions with the log of these variables on the left-hand side and the same variables as in equation (1) on the right-hand side.

[INSERT TABLE 6 ABOUT HERE]

Our findings are reported in Table 6. First, columns (1) to (4) show that deregulation has no significant effect on the number of patents per innovator. When interpreting this result, one must keep in mind that there is a composition effect as we count the number of patents conditional on the firm filing at least one patent. If deregulation causes small innovators to stop filing patents, then the number of patents filed by firms which stay in the innovation market mechanically increases. This may explain why the coefficient on the average number of patents per innovator is slightly positive although not significant (column (2)).

Second, columns (5) to (10) show that innovators produce more incremental and less risky patents. The average (median) number of citations decline by 3.2% (3.4%). The interpretation is that firms change their strategy and reallocate their projects toward more incremental innovations, which can be more easily evaluated by their creditors but are less valuable. We also find that the standard deviation of the number of citations declines by 2.7%. This is consistent with the notion that the most risky projects, which can lead to ground-breaking innovations but can also turn into complete failures, are more difficult to evaluate. Therefore, they face stronger difficulties to get financed when relationships are hurt.

3.2.2 The choice between R&D and fixed investment

Another consequence of hurting lending relationships is that firms should reallocate their investment plans towards projects which can be evaluated based on hard information. We test this prediction by comparing the effect of deregulation on investment in R&D and investment in capital assets. R&D investment is by nature opaque and difficult to evaluate. It requires the lender to spend time and effort collecting soft information about the borrowing firm to assess the real potential of an innovative project. By contrast, information about investment in capital assets is more easily verifiable by an arm's-length lender. In addition, it has greater value as collateral.

We obtain accounting information from Compustat, which implies that we now restrict our attention to public firms. We exclude financial firms because they are directly affected by banking reforms. Table 1, Panel C reports summary statistics on the variables considered in the empirical analysis. R&D expenses averages to 3.3% of total assets and are nonzero for 35% of firm-year observations. Investment in physical assets is measured by the change in net property, plant, and equipment (PPE), which averages to 2.4% of total assets.

We regress R&D spending and change in PPE (both normalized by total assets) on the deregulation index as well as on the same set of controls and fixed effects as in equation (1).[19] Results are reported in Table 7.[20] Column (1) shows that R&D decreases by about 0.5% of total assets, which represents a 16% decline. By contrast, column (3) indicates that investment in physical capital increases following deregulation: change

[19] Results are similar when using a Tobit model for R&D spending.

[20] Since we now work at the firm level, we could control for usual firm-level determinants of investment. However, such variables are likely to be endogenous to investment. For instance, a firm's Q depends on its ability to finance investment. It implies that including these variables in the regression could bias our results. Accordingly, we choose not to control for firm-specific time-varying variables. However, we have checked in untabulated regressions that adding such controls has little effect on the results.

in PPE rises by 0.29% of total assets, which represents a 12% increase. Therefore, we observe a reallocation of projects away from innovative projects and toward investments in hard assets. This reallocation is consistent with the hypothesis that hurting lending relationships impedes the financing of innovation but not the financing of more traditional types of investment.

[INSERT TABLE 7 ABOUT HERE]

We expect these reallocation effects to be stronger for more credit constrained firms, while large firms which can easily issue bonds and commercial paper should to be less affected by banking deregulation.[21] Accordingly, we use size as a proxy for banking dependence. In every year over the sample period, we classify firms into three terciles of the annual distribution of total assets. We interact the three terciles with the deregulation index, as well as with the controls and fixed effects as explained in Section 3.1.2.

In columns (2) and (4) of Table 7, we find that deregulation has no effect on investment in R&D and investment in physical assets in the top tercile of firm size (the reference group). This result is consistent with the idea that large firms are not dependent on local banking markets and are thus not directly affected by banking deregulation. Moreover, the effect of deregulation increases monotonically with firm size and the difference between the bottom tercile and the top tercile is significant at the 5% level, both for R&D and for change in PPE. Therefore, the reallocation of investment from hard information intensive projects toward soft information ones is concentrated in small firms, which are more likely to be dependent on bank lending than large firms.

[21] Only 18% of firms have a credit rating during the 1985-1998 period (information is not available prior to 1985). Therefore, the median firm in Compustat is likely to be dependent on bank financing.

3.3 Impact on industrial specialization

Finally we draw a bridge between our micro-level evidence and macroeconomic effects. Since deregulation reshapes the comparative advantage of the banking system toward financing hard information industries and away from innovative ones, it may also affect the specialization of the real economy.

To test this idea, we obtain annual value added data by state and industry from the Bureau of Economic Analysis (BEA). The data cover the whole spectrum of economic activity. After excluding sectors in the "Agriculture, forestry, and fishing" and "Finance, insurance, and real estate" categories as well as private households, we end up with 49 industries.[22] We compute at the state-year-industry level the share of the industry in total state GDP.

We create two measures of industry-level innovation intensity.[23] The first one is defined at the industry-year level as the number of patents filed in this industry all over the U.S. over a five-year rolling window divided by industry value added. Following Acharya and Subramanian (2009) this proxy for innovation intensity is time varying to account for the fact that the distribution of patents across industries has changed over time (see Figure 5 in Hall, Jaffe, and Trajtenberg, 2001). In addition, the proxy is computed as the average innovation intensity at the U.S. level rather than state by state to make sure that it is not endogenous to state-specific trends.

Our second proxy is constructed from the National Survey of Small Business Finance (NSSBF) and is defined as the share of employees devoted to R&D activity averaged by industry at the U.S. level for the reasons outlined previously.[24] Relying on the NSSBF

[22]We exclude 1998 from the sample period as there is a change in the BEA industry classification system in this year.

[23]We describe in more details how we construct these variables in Appendix A.3.

[24]The second proxy is not time-varying as the number of employees devoted to R&D is only available in the 1993 survey. In addition, we lose three industries when working with the second proxy because "Mem-

allows us to measure the innovation of small and private firms, while our first proxy focuses on public firms. The correlation between these our proxies is only equal to 25%, which may be explained by the fact that they are based on quite different types of firms.

Finally, we decompose the two measures of industry-level innovation intensity into terciles. We regress the share of each industry in total state GDP on deregulation and its interaction with these terciles, as well as on the same set of controls and fixed effects as in our previous regressions.

[INSERT TABLE 8 ABOUT HERE]

Results are reported in Table 8. In columns (1) and (2), we find that the share of the most innovative industries decreases by 0.096 percentage points relative to the least innovative industries when innovation intensity is proxied by patents filled by public firms. Given that the average share of a given industry is $1/49 \approx 2\%$ (there are 49 industries), it implies that the share of the most innovative industries experiences a relative decline of 4.7% as compared to the least innovative industries. In columns (3) and (4), we find similar results when innovation intensity is proxied by R&D employment in small private firms.

We therefore identify a novel channel through which financial environment can affect the specialization of the economy: credit markets characterized by relationship lending promote innovative sectors while arm's length credit markets have a comparative advantage toward more traditional industries. This complements Brown and Martinsson (2012)'s finding that equity market development leads to a specialization into high-technology sectors. Overall, these results suggest that financial environment, by determining the nature of information produced by financiers, shapes comparative advantages.

bership organizations", "Pipelines, except natural gas", and "Tobacco products" are not represented in the NSSBF.

3.4 Robustness

This section presents additional tests of our baseline result, namely, that the number of innovators decreases following deregulation.

3.4.1 University innovators

Alternative explanations of our results could be that the change in innovation we document is due to other state-level contemporaneous shocks, or that deregulation is endogenous to innovation activity. Ruling out these possibilities requires to find a group of innovators which are not affected by banking reforms and look at whether their innovation activity changes following deregulation. Universities provide such a group as they does not a priori depend on bank credit. The NBER Patents File identifies patents filed by universities (which we have excluded from our analysis so far). We re-run our baseline regression replacing the number of corporate innovators by the number of university innovators as the dependent variable. Results are reported in columns (1-2) of Table 9. Reassuringly, deregulation has no effect on university innovators.

[INSERT TABLE 9 ABOUT HERE]

3.4.2 Other robustness checks

We run a battery of other robustness checks. We perform a "placebo" test by re-assigning randomly the deregulation dates to the different states. We re-run our baseline regression and find no effect of these fake deregulations (columns (3) and (4) of Table 9).

We also control for the interstate banking reforms that took place during the 1980s. We define a dummy variable equal to one after a state permits interstate banking, that is, after a state allows banks from other states to buy its banks. First, we find that the effect of intrastate deregulation is not affected when we control for interstate deregulation (columns (5) and (6)). Second, interstate deregulation has a positive effect on innovation, but this effect vanishes once we include state-level control variables. This is consistent with our discussion in Section 2 that, in theory, interstate deregulation has two opposite effects on innovation: a competition effect which hurts relationships and reduces innovation, and a diversification effect which increases bank risk taking and fosters innovation. In another test, we restrict the sample period to 1968-1994 and exclude the period that follows the second wave of interstate deregulation starting with the passage of the Riegle-Neal Act in 1994. In this case, the effect of intrastate deregulation on innovation remains negative and significant (columns (7) and (8)).

Finally, we check that our results are not driven by the most innovative industries or by the most innovative states. Our results are mostly unchanged when we exclude the most innovative industries (columns (9) and (10)) and when we exclude the most innovative states (columns (11) and (12)).

4 Conclusion

Employing patent-, firm-, and industry-level data, we show that the nature of information that banks and firms can share conditions the comparative advantages of the economy. Specifically, when lending relationships are hurt, we find that the number of innovators decreases, especially in sectors in which firms communicate with their lenders mainly through soft information; that innovation is more incremental; that firms do less R&D and invest more in physical assets; all of which entail a decline in the share of technologically innovative sectors.

Therefore, our paper provides insight into the drivers of innovation and the capacity of an economy to finance its technologically innovative sectors. In particular, it shows that the ability of lenders to deal with soft information is crucial and that simply increasing the size of funding might not be sufficient if funds are allocated at arm's length. It also suggests that while reducing financial constraints for more established firms, the increase in competition for lending might lead to further tightening of financial constraints for innovative firms, thereby reshaping comparative advantages. This reallocation of investment does not necessarily slow down growth, especially in the short run. It will depend on whether the positive effect in traditional sectors is outweighed by the negative effect in innovative sectors. However, given that innovation generates spillovers, the reshape of comparative advantages might impede long-run growth.[25]

In term of public policies, if one accepts that the lesson drawn from commercial banking extends to public funding, then our research suggests that governments willing to support innovation by allocating public funds should not rely on a centralized and hierarchical structure, but on the contrary on local agencies, more able to deal with soft information.

Finally, our results shed some light on the drivers of comparative advantages around the world. For example, one puzzle in Europe is why France lags behind Germany in high technology sectors. The structure of their respective banking markets offer a sensible explanation. Whereas France is dominated by a small number of large national banks, Germany is characterized by multiple regional banks with close relationships with their debtors.

[25]Evidence of the effect of banking deregulation on economic growth are mixed; see, e.g., Jayaratne and Strahan (1996) and Huang (2007).

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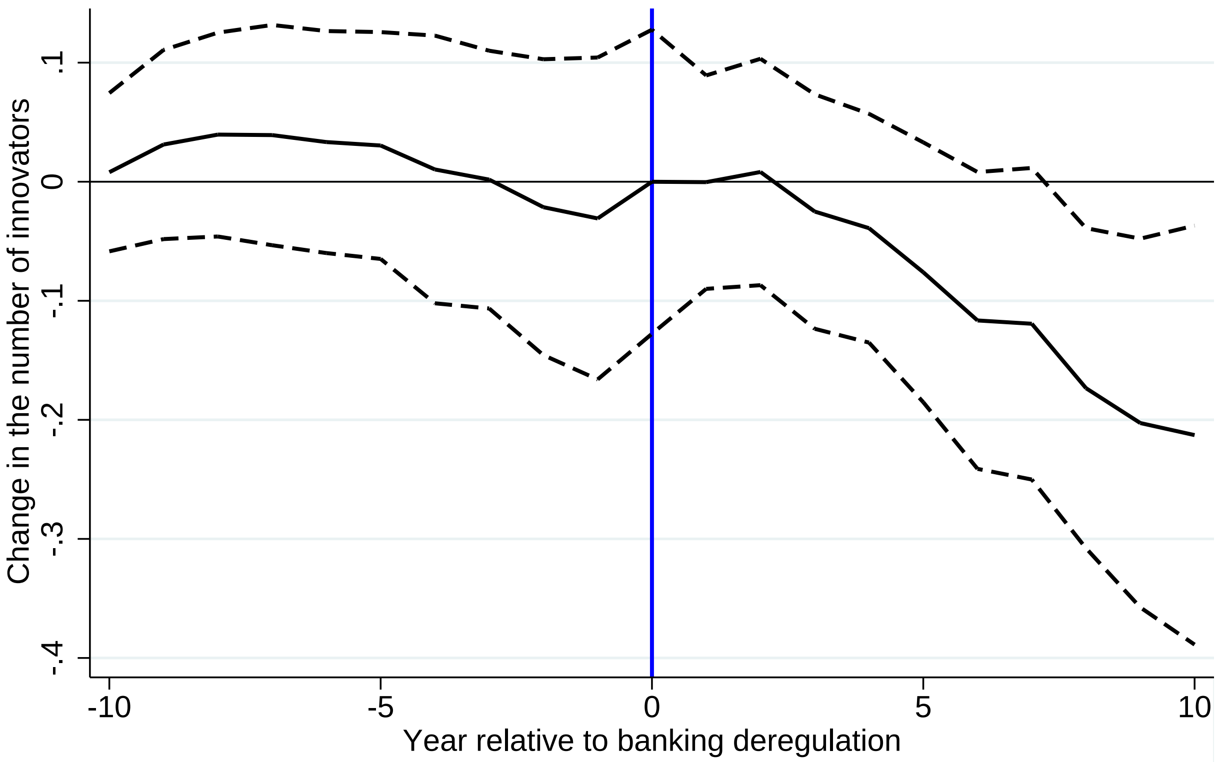
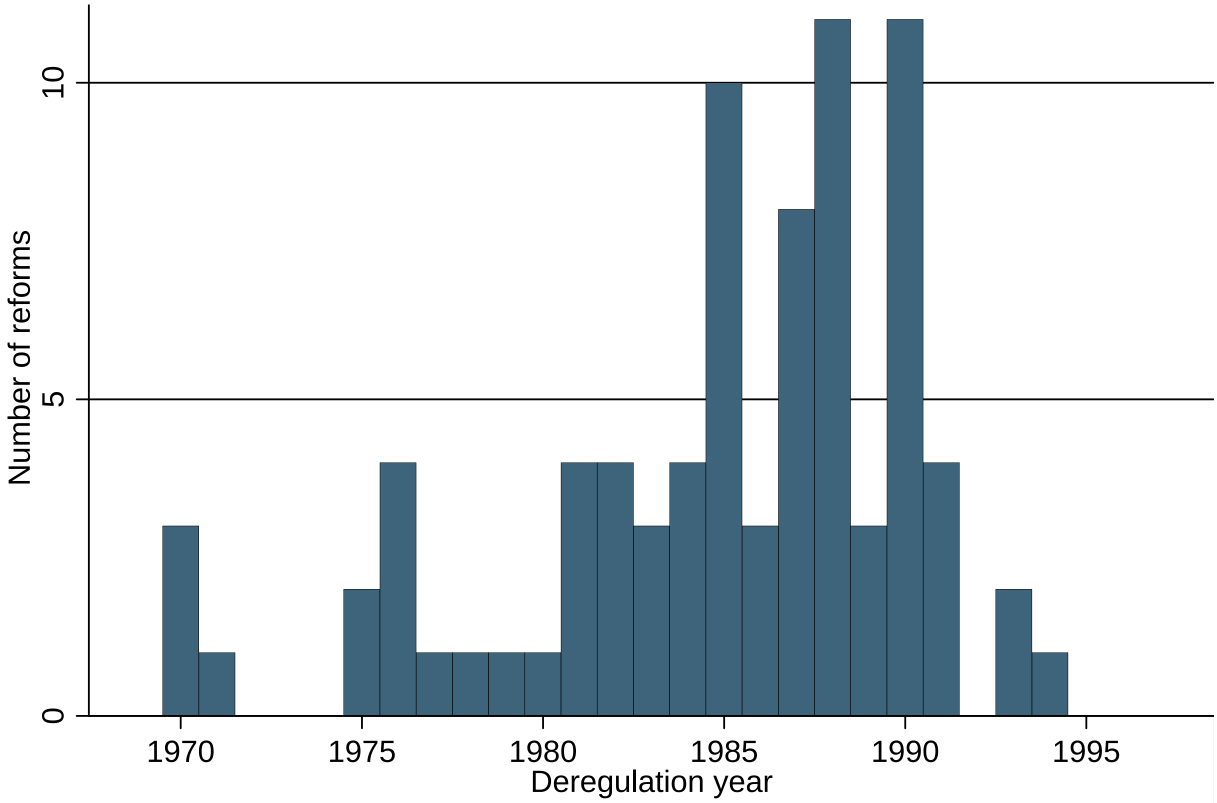
Figure 1: Effect of banking deregulation on innovation



Note: The figure shows the evolution of innovation around deregulation dates. The specification is the same as equation (1) except that the deregulation index is replaced by dummy variables $I(k)$ equal to one exactly k years after (or before if k is negative) the state allows intrastate branching through mergers and acquisitions. The solid line plots the point estimates of the dummy variables $I(k)$ for $k = -10, \ldots, 10$, where the deregulation year $k = 0$ is the reference year. The dashed lines plot the 95% confidence interval and standard errors are clustered at the state-level.

Figure 2: Timing of intrastate deregulation



Note: This graph shows the number of reforms constituting the Black and Strahan (2001)'s deregulation index that took place each year of the sample period. The reforms constituting the deregulation index are: a state allows the formation of multibank holding companies; branching by M&A; unrestricted (de novo) branching.

Table 1: Summary statistics

Panel A: Number of innovators per industry (NBER Patents File)						
	Obs.	Mean	Std.Dev.	25th	50th	75th
All industries	57,350	5.6	13	0	1	5
Agriculture, food, and textiles	1,550	1	1.6	0	0	1
Coating	1,550	3.1	4.8	0	1	4
Gas	1,550	1.3	2	0	1	2
Organic compounds	1,550	2.6	5	0	1	3
Resins	1,550	3.8	5.8	0	1	5
Other chemical	1,550	20	28	3	9	24
Communications	1,550	9.2	20	1	3	10
Computer hardware and software	1,550	5.4	17	0	1	5
Computer peripherials	1,550	1.6	6.4	0	0	1
Information storage	1,550	2.2	8.8	0	0	1
Other computers and communications	1,550	1.3	5.2	0	0	1
Drugs	1,550	6.7	18	0	1	5
Surgery and medical instruments	1,550	8	19	0	2	9
Biotechnology	1,550	.34	.97	0	0	0
Other drugs and medical	1,550	1.5	3.8	0	0	2
Electrical devices	1,550	6.6	11	0	2	7
Electrical lighting	1,550	2.9	6.2	0	1	3
Measuring and testing	1,550	7	12	1	3	8
Nuclear and X-rays	1,550	2.6	5.9	0	1	3
Power systems	1,550	6.1	9.9	0	2	8
Semiconductor devices	1,550	1.4	6.1	0	0	1
Other electrical and electronic	1,550	4.6	8.2	0	2	5
Material processing and handling	1,550	14	19	2	7	19
Metal working	1,550	7.2	11	1	3	8
Motors and engines	1,550	6.2	9.4	0	2	8
Optics	1,550	2.1	5.1	0	0	2
Transportation	1,550	6.2	9.1	1	3	8
Other mechanical	1,550	13	19	2	6	17
Agriculture, husbandry, and food	1,550	5.8	7.6	1	3	8
Amusement devices	1,550	2.4	4.6	0	1	3
Apparel and textile	1,550	3.8	5.4	0	2	5
Earth working and wells	1,550	3.8	8.3	0	1	4
Furniture and house fixtures	1,550	6	8.7	0	2	8
Heating	1,550	3.7	4.9	0	2	5
Pipes and joints	1,550	2.9	4.8	0	1	3
Receptacles	1,550	6.5	9.6	1	3	9
Miscellaneous	1,550	24	33	3	10	32

Note: Panel A reports summary statistics on the number of innovators at the state-year-industry level by industry.

Table 1: Summary statistics (continued)

Panel B: Innovators and patents (NBER Patents File)						
	Obs.	Mean	Std.Dev.	25^{th}	50^{th}	75^{th}
Innovator age	301,553	5.7	7.1	0	3	8
Industry age	301,553	3.6	1.6	3	3	5
Patents per innovator	324,195	4	24	1	1	2
Citations per patent	1,152,810	11	16	3	6	13
Panel C: Public firms (Compustat)						
Total assets	149,102	729	4,449	12	51	256
R&D / Total assets	149,102	.033	.099	0.00	0.00	0.02
Positive R&D	149,102	.35				
R&D/Total assets cond. on positive R&D	51,504	.096	.15	0.02	0.05	0.11
ΔPPE / Total assets	149,102	.024	.11	-0.01	0.02	0.06

Note: Panel B reports summary statistics at the innovator-year level and at the patent level; *Innovator age* is the numbers of year since the innovator first filed a patent application; *Industry age* is the median of *Innovator age* across all innovators in the industry (both age variables are defined starting in 1970 to limit truncation problems); *Patents per innovator* is the number of patents filed by the innovator in a given year; *Citations per patent* is the total number of citations received by the patent. Panel C reports summary statistics about all Compustat firms at the firm-year level: *Positive R&D* equals one if the firm has strictly positive R&D expenses; *R&D/Total assets cond. on positive R&D* is R&D normalized by total assets defined only when R&D is positive.

Table 2: Effect of banking deregulation on innovation

Dependent variable:	Number of innovators					
	(1)	(2)	(3)	(4)	(5)	(6)
Deregulation	-.097***	-.072**	-.071**	-.071**		
	(.036)	(.036)	(.036)	(.036)		
Deregulation (≤t-5)					.028	.024
					(.034)	(.032)
Deregulation (t-4,t-1)					-.012	-.016
					(.02)	(.018)
Deregulation (t+1,t+4)					-.032***	-.027***
					(.0094)	(.0096)
Deregulation (≥t+5)					-.12***	-.09***
					(.032)	(.025)
College graduates		.54***	.5**	.51***		.54***
		(.21)	(.2)	(.2)		(.19)
PhD graduates		.47***	.47***	.43**		.36**
		(.18)	(.18)	(.18)		(.15)
R&D federal expenses			.041	.045		.046
			(.044)	(.042)		(.044)
VC funds				.027**		.029**
				(.013)		(.013)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,350	57,350	57,350	57,350	57,350	57,350
Pseudo-R2	.73	.73	.73	.73	.73	.73

Note: 50 U.S. states, 37 industries, 1968-1998. We estimate a Poisson model in which the dependent variable is the number of innovators at the state-industry-year level. All regressions include state, year and industry fixed effects. In column (1) the only explanatory variable is the deregulation index which ranges from 0 (full regulation) to 3 (full deregulation). In column (2) we add the number of the state-year-level number of college degrees granted and number of doctorates granted. In column (3) we add the state-year-level amount of federal R&D spending. In column (4) we add the state-year-level dollar amount of invested VC capital. In columns (5) and (6) we split the deregulation index into four sub-periods. Standard errors are clustered at the state-level.

Table 3: Effect of banking deregulation on innovation: interaction with credit constraint

Dependent variable:	Number of innovators			
	(1)	(2)	(3)	(4)
Deregulation	-.034	-.015	-.02	-.0023
	(.022)	(.016)	(.023)	(.023)
Deregulation × Intermediate financial dependence	-.041	-.032		
	(.034)	(.026)		
Deregulation × High financial dependence	-.11*	-.096**		
	(.061)	(.048)		
Deregulation × Intermediate collateral			-.033***	-.028***
			(.01)	(.0097)
Deregulation × Low collateral			-.13***	-.12***
			(.044)	(.036)
Controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	57,350	57,350	57,350	57,350
Pseudo-R2	.76	.76	.76	.76

Note: 50 U.S. states, 37 industries, 1968-1998. We estimate a Poisson model in which the dependent variable is the number of innovators at the state-industry-year level. All regressions include state, year and industry fixed effects, and even-numbered columns also include the same set of state-year control variables as in Table 2. In columns (1) and (2) the deregulation index, the state and year fixed effects and the control variables (when included) are interacted with the terciles of industry-level dependence on external finance. In columns (3) and (4) they are interacted with the terciles of industry-level fraction of tangible assets. Standard errors are clustered at the state-level.

Table 4: Effect of banking deregulation on innovation: interaction with age

Dependent variable:	Number of innovators in age category					
	(1)	(2)	(3)	(4)	(5)	(6)
Deregulation	-.054	-.042	-.01	-.002	.025	.025
	(.048)	(.045)	(.031)	(.029)	(.04)	(.036)
Deregulation × Young innovator	-.069**	-.051*			-.067**	-.049**
	(.033)	(.027)			(.03)	(.024)
Deregulation × Young industry			-.091***	-.075***	-.096***	-.079***
			(.023)	(.017)	(.022)	(.017)
Controls	No	Yes	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes
Observations	107,300	107,300	107,300	107,300	107,300	107,300
Pseudo-R2	.68	.69	.46	.46	.69	.69

Note: 50 U.S. states, 37 industries, 1970-1998. We estimate a Poisson model in which the dependent variable is the number of innovators at the state-industry-year-age category level, where the two age categories are young innovators (less than or equal to 3 years) and old innovators (more than 3 years). All regressions include state, year and industry fixed effects, and even-numbered columns also include the same set of state-year control variables as in Table 2. In columns (1) and (2) the deregulation index, the state and year fixed effects and the control variables (when included) are interacted with the young innovator category dummy. In columns (3) and (4) they are interacted with the with the young industry dummy. In columns (5) and (6) all interaction terms are included. Standard errors are clustered at the state-level.

Table 5: Effect of banking deregulation on innovation: interaction with nature of information

Dependent variable:	Number of innovators					
Proxy nature of info:	Distance with lender		Increase in distance with lender		Length of relationship with lender	
	(1)	(2)	(3)	(4)	(5)	(6)
Deregulation	-.089*	-.066	-.083**	-.06	-.046*	-.023
	(.048)	(.046)	(.041)	(.042)	(.024)	(.025)
Deregulation × Intermediate soft	.045	.043	-.006	-.0014	-.038***	-.039***
information intensity	(.043)	(.035)	(.017)	(.016)	(.014)	(.013)
Deregulation × High soft	-.068***	-.052***	-.042***	-.038**	-.11***	-.11***
information intensity	(.019)	(.016)	(.015)	(.016)	(.038)	(.03)
Controls	No	Yes	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,350	57,350	57,350	57,350	57,350	57,350
Pseudo-R2	.75	.75	.74	.74	.75	.75

Note: 50 U.S. states, 37 industries, 1968-1998. We estimate a Poisson model in which the dependent variable is the number of innovators at the state-industry-year level. All regressions include state, year and industry fixed effects, and even-numbered columns also include the same set of state-year control variables as in Table 2. In all regressions the deregulation index, the state and year fixed effects and the control variables (when included) are interacted with the terciles of industry-level reliance on soft information. In columns (1) and (2) soft information is proxied by (minus) average distance from main lender; in columns (3) and (4) it is is proxied by (minus) average change in distance from main lender; in columns (5) and (6) it is proxied by average length of relationship with main lender. Standard errors are clustered at the state-level.

Table 6: Effect of banking deregulation on quality of innovation

Dependent variable:	Average patents per innovator		Median patents per innovator		Average citations per patent		Median citations per patent		Std. dev. citations per patent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Deregulation	.034	.033	.011	.0066	-.035***	-.032***	-.036***	-.034***	-.031**	-.027**
	(.022)	(.023)	(.012)	(.011)	(.0092)	(.0091)	(.0083)	(.0085)	(.013)	(.012)
College graduates		-.11		-.15**		.05		.019		.092
		(.099)		(.072)		(.066)		(.072)		(.081)
PhD graduates		.073		.05		.027		.035		.049
		(.095)		(.058)		(.049)		(.054)		(.064)
R&D federal expenses		-.016		-.04**		.012		.0072		.0032
		(.021)		(.015)		(.013)		(.013)		(.017)
VC funds		-.0073		-.014*		.0063		.0006		.016
		(.0085)		(.007)		(.0084)		(.008)		(.01)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,013	23,013	23,013	23,013	23,013	23,013	23,013	23,013	23,013	23,013
Adjusted-R2	.19	.19	.21	.21	.57	.57	.53	.53	.44	.44

Note: 50 U.S. states, 37 industries, 1968-1998. In columns (1) and (2) the dependent variable is the average number of patents per innovator at state-industry-year level; in columns (3) and (4) it is the median number of patents per innovator; in columns (5) and (6) it is the average number of citations per patents; in columns (7) and (8) it is the median number of citations per patents; in columns (9) and (10) it is the standard deviation of the number of citations per patents. All regressions are linear regressions. The explanatory variables are the deregulation index, state, year and industry fixed effects, and even-numbered columns also include the same set of state-year control variables as in Table 2. Standard errors are clustered at the state-level.

Table 7: Effect of banking deregulation on investment in R&D and in physical assets

Dependent variable:	R&D		Δ PPE	
	(1)	(2)	(3)	(4)
Deregulation	-.0053**	-.00074	.0029*	.00092
	(.0025)	(.00077)	(.0016)	(.0014)
Deregulation × Medium		-.0035**		.0032**
		(.0017)		(.0013)
Deregulation × Small		-.0066**		.0038**
		(.0033)		(.0016)
Constant	.21*	.22	.08	.053
	(.11)	(.13)	(.063)	(.063)
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	152,462	152,462	152,462	152,462
Adjusted-R2	.26	.29	.036	.053

Note: All non-financial Compustat firms, 1968-1998. In columns (1) and (2) we run an OLS regression in which the dependent variable is R&D expenses divided by total assets; in columns (3) and (4) the dependent variable is change in net property, plant and equipment divided by total assets. The explanatory variables are the regulation index, state, year and industry fixed effects, as well as the same set of state-year control variables as in Table 2. In even-numbered columns, the deregulation index, the state and year fixed effects and the control variables are interacted with the terciles of total assets. Standard errors are clustered at the state-level.

Table 8: Effect of banking deregulation on state comparative advantages

Dependent variable:	Industry share of state GDP			
Proxy industry innovation intensity:	Patents		R&D employment (NSSBF)	
	(1)	(2)	(3)	(4)
Deregulation	.00027	.00031	.00029	.00023
	(.00019)	(.00019)	(.00023)	(.00019)
Deregulation × Intermediate	.00025	0.00001	0.00087	.00024
innovation intensity	(.00039)	(.00031)	(.0003)	(.00026)
Deregulation × High	-.0011**	-.00096**	-.00096*	-.00095*
innovation intensity	(.00046)	(.00046)	(.00053)	(.00049)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	73,500	73,500	69,000	69,000
Adjusted-R2	.63	.63	.64	.64

Note: 50 U.S. states, 49 industries (columns (1)-(2)) or 46 industries (columns (3)-(4)), 1968-1997. We estimate a linear model in which the dependent variable is the industry-state-year value added divided by the state-year value added. In columns (1) and (2) industry-level innovation intensity is the time-varying number of patents filed in the industry over all the U.S. divided by industry GDP. In columns (3) and (4) industry-level innovation intensity is the average fraction of employees doing R&D from the 1993 National Survey of Small Business Finance. All regressions include state, year and industry fixed effects, and even-numbered columns also include the same set of state-year control variables as in Table 2. The deregulation index, the state and year fixed effects and the control variables (when included) are interacted with the terciles of industry-level innovation intensity. Standard errors are clustered at the state-level.

Table 9: Effect of banking deregulation on innovation: robustness

Dependent variable:	Number of innovators											
	Dep. var. = university innovators		Random deregulation dates		Interstate banking deregulation		Exclude after 1994		Excl. most innovative industries		Excl. most innovative states	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Deregulation	-.00074	.026	.016	.029	-.098***	-.072**	-.064**	-.044*	-.11**	-.085**	-.11**	-.061*
	(.057)	(.05)	(.046)	(.042)	(.036)	(.036)	(.027)	(.026)	(.045)	(.042)	(.044)	(.038)
Interstate banking					.056**	.014						
					(.025)	(.021)						
College graduates		.68		.45*		.51***		.31		.47**		.85***
		(.44)		(.26)		(.2)		(.22)		(.23)		(.18)
PhD graduates		.69**		.58**		.43**		.37**		.5**		-.034
		(.27)		(.25)		(.18)		(.16)		(.21)		(.12)
R&D federal expenses		.062		.056		.045		.077**		.029		.037
		(.065)		(.043)		(.042)		(.033)		(.048)		(.036)
VC funds		-.054		.026**		.027**		.022		.033**		.029**
		(.034)		(.013)		(.013)		(.014)		(.015)		(.014)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,350	57,350	57,350	57,350	57,350	57,350	49,950	49,950	51,150	51,150	49,321	49,321
Pseudo-R2	.38	.39	.73	.73	.73	.73	.73	.74	.65	.66	.65	.65

Note: 50 U.S. states, 37 industries, 1968-1998. We estimate a Poisson model in which the dependent variable is the number of innovators at the state-industry-year level. The explanatory variables are the deregulation index, state, year and industry fixed effects, and even-numbered columns also include the same set of state-year control variables as in Table 2. In columns (1) and (2) the dependent variable is replaced by the number of university innovators. In columns (3) and (4) the deregulation index is replaced by a "placebo" deregulation index computed from random deregulation dates. In columns (5) and (6) we add a dummy equal to one if the state has started to implement interstate banking deregulation. In columns (7) and (8) we restrict the sample period to 1968-1994. In columns (9) and (10) we exclude "Other mechanical", "Material processing and handling", "Other chemical" and "Miscellaneous industries". In columns (11) and (12) we exclude California, Massachusetts, New York, Ohio, Pennsylvania, New Jersey and Texas. Standard errors are clustered at the state-level.

A Construction of variables

A.1 Financial dependence and collateral

We start from Compustat and keep all non-financial firms during the sample period 1968-1998. We compute firm-level external dependence as investment (capital expenditure (item #128) + R&D expenses (item #129) + acquisitions using cash (item #46)) minus ROA (item #13) divided by investment, and we take the mean across all firms and years at the 3-digit SIC level. We cannot use directly this variable in our regressions because patent data use a different industry classification. Instead, we start from the NBER Patents File and match public innovators with Compustat (the patent data include the GVKEY of public innovators) in order to obtain the 3-digit SIC-level external dependence variable defined in the first step. Finally, we average this variable across all public innovators and years in each of the 37 industry classes used in our regressions.

The collateral variable is constructed in a similar way. Firm-level collateral is defined as property, plant and equipment (item #7) divided by total assets (item #6).

A.2 Soft information intensity

We use the National Survey of Small Business Firms (NSSBF) which is available on the Fed website. To construct the first proxy of soft information, we compute the average distance from the main lender in the 1987 survey (variable r6481) by two-digit SIC industry. We then use the same procedure described in Appendix A.1 to map this variable into the NBER Patents File industry classification: we assign the two-digit SIC-level variable to Compustat firms, match Compustat firms which file patents with patent data, and average the above-mentioned variable at the NBER industry level.

To construct the second proxy of soft information, we compute the average distance from the main lender in the 1998 survey (variable idist1) by two-digit SIC industry. Then, we compute the growth rate of average distance from main lender between 1987 and 1998 and map this variable into the NBER Patents Files industry classification.

Our third proxy is the average length of relationship with the main lender. Note that length of relationship is mechanically correlated with firm age, since only an old firm can already have a long-standing relationship with its bank. Besides, we know from Table 4 that banking deregulation has a stronger effect on younger firms. Therefore, if we want to assess the effect of length of relationship, we need to filter out the age component from that variable. To do that, we regress log of length of relationship in the 1987 survey (variable r3311) on log of firm age (1987 minus foundation year, variable r1008) at the firm-level: $\log(Length_i) = a + b.\log(Age_i) + \varepsilon_i$, and we compute the age-adjusted length of relationship as $\log(Length_i^{Adj}) = \log(Length_i) - \hat{b}.(\log(Age_i) - \overline{\log(Age)})$ where the upper bar denotes the sample average. We then proceed as for the first two proxies: average over two-digit SIC industry and map into NBER patent industry classes.

A.3 Innovation intensity

To define our first proxy of innovation intensity, we merge the patents filed by public firms (whose GVKEY is provided in the NBER Patents File) with Compustat to obtain the SIC classification of the innovator. For each two-digit SIC industry and each year, we count the number of patents filed by public firms in this industry over the past five years. We then use correspondence table between the SIC classification and the BEA classification to obtain the number of patents by BEA industry, and we divide by the industry's value added obtained from the BEA data to obtain the innovation intensity at the BEA industry-year level.

To defined our second proxy of innovation intensity, we use the 1993 National Survey of Small Business Firms. We compute the firm-level fraction of employees devoted to R&D activity (variable b13_5 divided by b11 plus b13) and then compute the two-digit SIC average.