Banking on Innovation: The Impact of U.S. Bank Deregulation on the Production of Knowledge*

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March 4, 2012

Abstract

This paper provides causal evidence that financial market development directly affects innovation by studying bank deregulation in the United States. I find that patenting increases significantly after intrastate banking reforms. I also find that the effect is more pronounced among relatively less novel and less complex innovations, consistent with a model of a credit market in which innovators have asymmetric information about the riskiness of their projects. The evidence suggests that financial development both increases the rate of innovation and affects its direction.

1 Introduction

A large literature has established a causal effect of financial development on growth. A theoretical literature in the endogenous growth tradition posits that this growth occurs because better financial markets more efficiently allocate capital for innovation, a proposition that goes at least as far back as Schumpeter (King and Levine, 1993b). Unlike technology-push and demand-pull models of innovation, these theories emphasize a distinct and important role for financial development in driving innovation.

*I am very grateful to Mitchell Petersen, Thomas Hubbard, Meghan Busse, and especially my committee chair Shane Greenstein for their guidance and advice.

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However, to date little causal evidence has been established demonstrating the posited effect of financial development on innovation, which is a necessary condition for this theoretical mechanism to work. Presumably, progress has been hindered by the likely endogeneity of financial development and innovation. In order to address the shortcomings in our understanding of the effect of financial market development on innovation, we use US patent data from 1976 to 1997, covering a period of extensive state banking reforms which relaxed restrictions on geographical expansion by banks. We study how bank branch deregulation affected patenting and how these effects varied across counties at different levels of urbanization and across different kinds of innovative activity.

The identification challenge is that technological opportunities tend to be geographically localized (Jaffe, Trajtenberg, and Henderson, 1993). Therefore, changes in innovative activity across regions around periods of financial development *are not* sufficient to establish causality. Our approach exploits the fact that US patent data identify whether a patent application is filed by an employee of a corporation or independent inventor, who patents on his own behalf. Without direct corporate backing, independent inventors are much more likely to be dependent on banks for financing. Thus, changes in a region's banking market should affect independent inventors more than corporate inventors. Comparing changes in patenting between independents and corporations *within* regions allows us to overcome concerns about correlation between the locations of deregulation and technological opportunity.

We find evidence of statistically significant and economically substantial increases in patenting after five years states deregulated their banking systems. These increases persisted nine years and onward, suggesting that the effect of banking reforms on patenting were not driven by mean revision or anticipation of reform.

We find that the effects are found in the subset of inventions that were less novel and less complex by standard patent-based metrics. We also find that the benefits of deregulation were not uniformly distributed: new inventors in noncentral counties benefited the most from deregulation. Together, these findings are consistent with a model in which increased competition in banking increases access to capital constrained innovators, but only those in regions with the largest distortions in banking like noncentral counties, and only for projects where ex-ante information asymmetries about the distribution of payoffs is less important, such as those that are less novel and less complex.

This paper adds to the literature on financial development and growth. While is a large literature on the finance and growth connection (e.g. King and Levine, 1993a; Jayaratne and Strahan, 1996; Rajan and Zingales, 1998), the microeconometric evidence for how financial development translates into growth is sparse. Most research on the mechanisms by which financial development affects growth has focused on new business creation (e.g. Black and Strahan 2002; Guiso, Sapienza, and Zingales, 2004; Kerr and Nanda, 2009) and on firm R&D (Brown, Fazzari, and Petersen 2009). Benfratello, Schiantarelli, and Sembenelli (2008) find that banking development increases process innovation but not product innovation on a sample of Italian manufacturing firms. They do not, however, control for time-*varying* regional factors that could affect both innovation and banking development, which we argued are critical for studying innovation growth. Kortum and Lerner (2000) showed that a 1979 clarification of the prudent man rule allowing pension funds to invest in venture capital led to an increase in patenting. This policy change removed an important constraint on the volume of capital available to entrepreneurs. Our paper investigates a distinct mechanism from theirs. Branching deregulation opened regions to greater competition between banks but did not directly remove a constraint on the total amount of funds available for banks to lend. Indeed, Jayaratne and Strahan (1996) show that branching reforms affected loan quality but did not significantly affect commercial loan growth. Thus, this paper's focus is on the effect of removing allocative distortions on innovation, which is the central mechanism considered in theoretical models of finance and growth.

2 History of U.S. Bank Branching Deregulation

Our identification strategy exploits the unusual history of US bank branching deregulation for plausibly exogenous variation in financial development. The McFadden Act of 1927 clarified the authority of states over national banks' branching activities. States used this regulatory authority to restrict regional competition between banks. This enabled incumbent banks' to earn monopoly rents, which could then be extracted by the states through taxes and bank charter fees (Kroszner and Strahan, 2007). States also restricted out-of-state banks from operating branches within their state lines, since they did not receive charter fees from banks incorporated in other states.

Kroszner and Strahan (1999) argue that technological innovations in banking weakened the incentives of protected banks to continue lobbying to maintain restrictions on geographic expansion. The developments of the automatic teller machines, banking by mail and telephone, credit-scoring databases, and innovations in financial theory eroded the advantages to dominating a single geographic market.

As a result, bank branching deregulation occurred across states at different times beginning in the 1970s and continuing into the 1990s. Interstate deregulation allowed multibank holding companies to expand their operations across state lines by acquiring out-of-state banks. Intrastate deregulation allowed banks to expand branching within state lines, either by mergers and acquisitions, via *de novo* branching, or both. The political motives and technological innovations in the banking sector that caused banking deregulation are probably not in themselves causes of growth opportunities outside of banking. However, it is not obvious that they were not correlated with changes in broader technological opportunity. If, for example, advances in information technology could cause both the adoption of financial innovation and make innovators more productive.

In this paper, we focus on the effects of intrastate deregulation and its differential effects on independent and corporate patenting *within* regions. Prior studies have found that branching deregulation is associated with higher state growth rates and increased number of new business starts (Jayaratne and Strahan, 1996; Black and Strahan, 2002). We focus on intrastate deregulation in this paper because of the previous evidence that these had a more significant impact on the growth of small firms (Cetorelli and Strahan, 2006).

Given the two forms of intrastate deregulation, we model deregulation using the leading edge of intrastate branching reform[1]. Twelve states already had some form of intrastate

[1] This happens to coincide with the year of intrastate mergers and acquisitions reform, since these happened to always precede reforms allowing *de novo* branching.

deregulation in place by 1970, and the rest with the exception of one state deregulating in some year between 1970 and 1997.

3 Analytical Framework

The goal of this section is to develop some intuition about how a change in the market structure of the banking industry might affect innovation. These intuitions are derived more formally in the theory appendix.

Consider a set of risk neutral firms seeking to borrow from a bank to finance a single innovative project with uncertain payoffs. A fraction of projects β are "safe" and succeed for sure and a fraction $1-\beta$ are "risky" and succeed with some probability less than one. Assume that all projects yield the same expected return. Stiglitz and Weiss (1981) showed that if the bank is restricted to offering debt contracts and has constant marginal costs, and firms have asymmetric information about the riskiness of its project, then banks will face an adverse selection toward risky projects. Banks face a tradeoff between setting a higher interest rate and the riskiness of the pool of borrowers that apply.

When entry restrictions are relaxed, interest rates on loans fall to a weakly lower level. If β is close to one so that most projects are safe, then deregulation produces no change in innovation since the monopolist would have found it optimal to set a rate already low enough where all types apply for loans, even when he could not observe the riskiness of any given project. If β is close to zero so that most projects are risky, deregulation still produces no change, this time because the monopolist finds it optimal to set a high rate where only risky firms apply and competitive banks cannot break even setting a rate low enough where all firms apply. For some intermediate values of β, deregulation causes the rate to fall from a level where only risky firms apply for loans to one where all firms apply.

We propose that the level of β is influenced by the proposed project's technological novelty and complexity. Banks may not know the riskiness of any given project, but they may know that innovation in some markets and technologies are riskier than others. Innovations using a proven technology may have higher β than ones based on cutting edge technology. Our approach is to use patent-based metrics for inventions' novelty and complexity as a proxy for β and examine whether deregulation is consistent with our predictions. Applying our framework directly would imply that we should observe a smaller effect of deregulation on the least and most novel and complex innovations. Because our sample consists of patentable inventions, which by definition must be sufficiently non-obvious, the prediction for the smaller effect on the least novel and complex innovations is confounded by sample selection and is therefore an empirical question.

In practice, independent inventors credit constraints are a common concern. Construction of a prototype, hiring a patent lawyer, or filling a large purchase order often involve substantial up-front investments. Banks are typically discussed as an option for the latter stages of manufacturing and commercialization or when one has sufficient amounts of collateral.

There is a complementary literature that argues that competition in banking makes it hard for young and distressed firms to obtain financing because competition undermines long-term banking relationships. Petersen and Rajan (1995) find that small and young firms are more likely to obtain credit in monopolistic credit markets than under competition. Their argument is that if a firm can commit to remaining in a relationship with a lender, the lender can subsidize firms by backloading interest payments to future periods. Competition among lenders undermines the ability of firms to commit to one lender and therefore their ability to obtain credit. The mechanism we have outlined says that competition forces a reallocation of scarce capital to safer projects as banks compete away monopoly rents in safer projects before they do in riskier ones.

3.1 Did interest rates fall after bank deregulation?

Consistent with our analytical approach, Jayaratne and Strahan (1998) found that interest rates on loans fell after branching deregulation. States experienced a decline in interest rates by .3 percentage points following branching deregulation. Further, the authors find that the decrease in interest rates fell in two-thirds of deregulating states, indicating that the effect was a widespread phenomenon.[2]

[2]They also find that deposit interest rates did not increase following branching deregulation, which is consistent with our modeling approach of highlighting competition on the lending side.

Jayaratne and Strahan (1998) show that the decline in loan interest rates coincided with decreases in loan losses by .29 percentage points in the short run and .48 in the longer run, and operating costs by 4.2 percent in the short run and 8 percent in the longer run. While they argue that deregulation caused improvements in the banking system's efficiency with screening borrowers, our findings show that there may have been compositional changes within commercial lending as well.[3]

4 Empirical Strategy

We want to test for a causal relationship between financial development and innovation by studying how bank branch deregulation affected patenting. The identification challenge is that technological opportunities tend to be geographically localized (Jaffe, Trajtenberg, and Henderson, 1993). Therefore, changes in innovative activity across regions around periods of financial development *are not* sufficient to establish causality. If we can identify a set of firms that rely more heavily on local bank finance, we can test whether innovation increases faster among this set than others *within* the same region after deregulation, thereby separating changes patenting due to local finance from changes due to broad local factors.

To identify a subset of firms that rely more heavily on bank finance, we exploit the fact that US patent data identify whether a patent application is filed by an employee of a corporation or independent inventor, someone who invents on his own behalf. Without access to commercial paper, corporate bond, and equity markets, small firms like independent inventors are much more likely to be dependent on banks for financing (Cetorelli and Strahan, 2006). Comparing changes in patenting between independents and corporations within regions allows us to identify changes in patenting due to deregulation. If availability of bank finance is a binding constraint for some corporations in our data, the estimation procedure will *underestimate* the effect of bank deregulation on innovation.

Because our innovation outcome variables are all nonnegative, contain many observa-

[3]Our paper focuses on patentable innovations, which must exhibit a sufficiently high degree of novelty and non-obviousness. Thus, an increase in even the less novel and complex innovations in our sample may be a shift *toward* risk-taking when compared to the universe of potential commercial loans.

tions with values of zero, and are highly skewed, it would be inappropriate to use OLS on a simple log transformation of the dependent variable. Instead, we model the conditional mean of our innovation outcome variables as an exponential function. In practice, we estimate Poisson models with pseudo-maximum likelihood and compute standard errors robust to both the possibility that the data are not Poisson distributed. Parameter estimates are consistent as long as the conditional mean is correctly specified.

To examine the extent to which broad local factors may confound estimates of the effect of deregulation on innovation, we start by running the following difference-in-difference regression:

$$E[Patents_{cjti}|X_{cjti}] = exp(X_{cjti}\beta) = exp(\beta_1 Dereg_{ct} + \alpha_1 State_c + \alpha_2 Year_t + \gamma x_{cjti}) \quad (1)$$

where $Patents_{cjti}$ is the total number of patents filed for from county c, industry j, year t, by inventor type $i \in$ {independent, corporate}. $Dereg_{ct}$ is an indicator variable equal to one when a county's state has passed branching reforms. $State_c$ and $Year_t$ are state and year fixed effects. The vector x_{ctji} is a set of county-level controls. The difference-in-difference estimate of the causal effect of banking deregulation on innovation is $e^{\beta_1} - 1$, which is the percentage change in innovation after deregulation. We test if innovation in states is changing significantly in years prior to the date of actual deregulation, which is evidence that changes in broad local factors may be sources of bias in difference-in-difference estimates of the effect of deregulation.

We then estimate versions of the following difference-in-difference-in-difference regression:

$$\begin{aligned} E[Patents_{cjti}|X_{cjti}] &= exp(X_{cjti}\beta) \quad (2) \\ &= exp(\beta_1 Dereg_{ct} * Indpt_i + \delta_1 StateYear_{ct} \\ &+ \delta_2 IndptYear_{ti} + \delta_3 StateIndpt_{ci} \\ &+ \alpha_1 State_c + \alpha_2 Year_t + \alpha_3 Indpt_i + \gamma x_{cjti}) \end{aligned}$$

In this regression, state-year effects absorb unobservable state-level trends. The estimate of the effect of deregulation on innovation $e^{\beta_1} - 1$ is now identified based on changes in the difference of independent and corporate innovation across states over time. The identifying assumption is that conditional on observables, the trend in the difference between independent and corporate patenting in each county would change to the same extent apart from banking deregulation.

5 Data

To measure how bank deregulation affected innovation, we construct a panel data set of patenting and industrial activity across U.S. counties between 1976 and 1997.Precise sources for all our data are given in the data appendix. Data on patents granted between 1976 and 2006 are available from the NBER patent data project and Harvard Business School patent database. We identify the location of a patent using the cities of the inventors' residences. Patents are assigned to industries of manufacture using a probabilistic concordance that matches patent technology classes with industry SIC codes constructed by Brian Silverman. We aggregate the data up to the county-industry-year-type cell, where type identifies independent and corporate filers. We exclude patents filed by government entities from the analysis.

We combine these data with state and county level information to control for changes in counties' independent-corporate patenting gaps. We control for changes in county-level local labor force composition using annual and industry-level data on employment and number establishments by employment-size bins from County Business Patterns.We interact these variables with an indicator variable for independent inventor observations to allow characteristics of the local labor force to affect independent and corporate patenting differently. This captures the possibility, for example, that an increase in the number of small establishments in a region increases independent patenting more than corporate patenting.

Other labor force variables include the fraction of states' adults over 25 with a college degree, state unemployment rate, whether a county has a university in the top 90th percentile in terms of federal research funding, and per capita state R&D expenditure. We also control for changes in local wealth and demand using county per-capita personal income, state home price growth rates, and county population. Finally, we control for counties' degree of urbanization using USDA urban-rural continuum variables. Again, interactions with independent dummies are included in all regressions.

5.1 Controlling for Changes in Legal Regimes

Our sample period covers important legal developments that could potentially affect innovation and patenting by corporate and independent inventors differently. First, Kortum and Lerner (2000) showed that a 1979 clarification of the prudent man rule allowing pension funds to invest in venture capital led to an increase in patenting. This policy change removed an important constraint on the volume of capital available to entrepreneurs, in particular in those industries in which venture capital had already been active. If this benefited independent inventors more than corporate inventors, then our identification strategy could be compromised. We address this concern by reporting the results when we include industry-year-type effects to absorb the policy change.

Second, in 1982 the U.S. Court of Appeals for the Federal Circuit was created. This was a pro-patent court in comparison to the regional courts whose authorities it displaced (Landes and Posner (2004)). Because regional courts varied in their attitudes towards patents before 1982, the creation of the court could have been a bigger improvement in certain regions than others. We attempt to control for this using data gathered by Koenig (1978) on the decisions on patent cases across regional courts between 1953 and 1972. We include in all regressions an indicator variable equal to one after 1982 for independent patent in states with below the median level of favorable patent rulings as of 1977.

6 Descriptive Statistics

Tables 1 and 2 show descriptive statistics for our dependent variables, deregulations, and controls. Table 3 shows the distribution of independent and corporate patenting across states. Patenting activity varies substantially across regions. States with fewer mean annual patents are associated with higher fractions of independent inventor patents. Table 4 shows patenting by county urbanization. Central metropolitan counties are responsible for a larger fraction of innovative activity relative to similar populated fringe counties and less populated metropolitan counties. Interestingly, metropolitan counties with between 250,000 and 1,000,000 population account for more innovative activity than counties with more than 1,000,000 population but lie in the fringes of a metropolitan area. Perhaps surprisingly, urbanization does not appear to be associated with higher fractions of corporate patenting.

Table 5 shows there is also substantial variation in patenting across industries. Industrial machinery and equipment, electrical and electronic equipment, instruments and related products, and chemical and allied products compose a large fraction of all manufacturing patenting activity. Independent inventors account for a substantial fraction of patenting in most industries with the exception of chemical and allied products, reflecting the capital-intensive nature of these industries. Industries with higher levels of patenting do not appear to have substantially different fractions of corporate invention.

Figure 1 plots the log of the total number of independent and corporate patents in urban counties over time. Independent patenting accounts for about 16 percent of all manufacturing patenting in urban counties during this period, with this percentage decreasing over time. The aggregate dynamics of log patenting shown in figure 1 are broadly similar for corporate and independent invention, suggesting that they are similarly responsive to macroeconomic forces. [4]

We disaggregate by county and compute the change over 1976 to 1997 in the difference between log of total patents by independent and corporate entities, and plot this against the number of years that counties have deregulated their banks in Figure 2. The regression line reveals a clearly positive (and statistically significant) relationship between earlier deregulation and patenting activity by independent entities relative to corporate entities. This scatterplot forecasts our main result, which continues to hold after a variety

[4] There is a slight drop-off in patenting at the end of our sample due to truncation bias since we observe the locations of inventors only for patents granted before 1999.

of robustness tests.

7 Empirical Results

In Table 6 we report the results from simple difference-in-difference regressions to assess the potential for bias due to local factors coinciding with the timing of deregulation. The first column presents estimates using the full sample. There is no significant effect of deregulation on the full sample. 84 percent of patents granted are filed by corporations, so the finding of no effect in the full sample is consistent with our prior that corporate innovation is not sensitive to changes in the structure of bank branching.

Column (2) shows estimates of the same regression on the subsample of independent patents. Patenting increased after deregulation, but lead effects suggest that patenting had already been increasing in deregulating counties prior to the year of actual deregulation. This suggests that broad local factors driving innovation were present around the time of deregulation, potentially biasing difference-in-difference estimates of the effects of deregulation.

In Table 7 we show the results from our difference-in-difference-in-difference model. If the relationship between deregulation and innovation is not spurious, we expect to find that the product of deregulation and the independent dummy to have a positive coefficient. This is what we find. Column (1) shows that patenting increased by close to 23% between the fifth and eighth year after reforms, and continues to increase to 37% in patenting afterward.

Column (2) contains state-industry-year effects to absorb shifts in industrial activity across regions. We find that the magnitude of the effect is moderately reduced but the estimates still indicate a strong effect of deregulation on innovation. Patenting does not change significantly in the first to fourth year after deregulation, increases by 20% in the fifth to eighth year and then 30% afterward. The delayed effect is consistent with a time lag in entry of banks into new markets and in the innovation process itself. The effect persists over a period of over 9 years, making it unlikely the results are driven by mean revision or anticipation of reform. Column (3) includes industry-type-year effects to absorb changes in shifts in industry patenting activity between corporate and independent entities. If, for example, our estimates are picking up some of the effect of increased venture funding due to change in the prudent man rule, the estimated effect should be reduced. We find in column (3) that the estimates are almost identical to the ones in column (2), indicating that shifts in activity between corporate and independent innovation is not contributing to our results. Lead effects are generally statistically insignificant, suggesting that the difference-in-difference-in-differences model better separates the effects of deregulation from unobserved local factors.

Raw patent counts ignore quality differences across patents. It is possible that deregulation increased patenting but did not increase innovation by much if the newly patented inventions were mostly of poor quality. Weighting patents by the citations they receive is a standard way of accounting for differences in patent quality. Table 8 presents the same set of regressions as Table 7 with citation-weighted patents as the dependent variable. Column (2) shows that the effect on citation-weighted patents is of very similar magnitude as on unweighted patents, increasing by 20% in the fifth to eighth year and 28% forward. This suggests that innovative output, not only patenting, increased after deregulation. Again, lead effects are generally statistically insignificant and do not appear to show a strong trend before deregulation.

8 Impact Heterogeneity

8.1 Measuring Innovation Novelty and Complexity

The analytical framework discussed above suggests that the effects of deregulation should vary by the technological novelty and complexity of the innovation. As a proxy for innovation novelty and complexity, our approach is to use standard patent-based metrics. These metrics are derived from the citations and claims made on each patent. Citations are required as a way of defining the scope of the patent relative to prior art and claims are technical descriptions of what ideas are being protected from future infringement. Citations to more recent patents reflect components of the invention that rely on more novel technologies. We use the mean age difference between a patent and its backward citations, termed Mean Backward Citation Lag, as one measure of the novelty of the innovation's technological approach.

Inventors may achieve novelty by producing new combinations of possibly old ideas. We measure how widely dispersed a patent's backward citations is across technology classes to obtain the Originality measure, which is computed in the way suggested by Trajtenberg, Jaffe, and Henderson (1997). Patent i's originality index is equal to $1 - \sum_j^{n_i} s_{ij}^2$, where s_{ij} is the share of citations made by patent i to patent technology class j, and n_i is the total number of classes cited by i. The Originality index therefore ranges from 0 to 1, with 1 being the highest level of Originality.

We proxy for patent complexity by using the number of claims made on the patent. Inventors have strong incentives to describe their invention thoroughly in their claims to expand the scope of protection as much as possible. The number of claims on a patent should therefore be correlated with the overall complexity of the underlying invention.

If banks do not know the riskiness of any given project but believe that innovation with novel or complex technologies is riskier than others, then deregulation should have a weaker effect on the most novel or complex technologies.

8.2 Measuring Innovation Returns

We have modeled novel and complex projects as having higher variance in returns than safe ones. If the effects of deregulation are concentrated away from technologically novel and complex projects, then we should also expect the effects to be concentrated away from inventions yielding the highest returns ex-post.

We use the number of citations received from future patents as a proxy for the returns to an innovation. Hall, Jaffe, and Trajtenberg (2005) found that patent citations translate into firm market value, suggesting that patent citations is indeed a measure of returns captured by the firm.

We also consider another measure of returns, Generality, which measures how widely dispersed the patent is cited across technology classes.[5] General inventions are ones that have contributed to many other technological fields, so the social value of the knowledge is likely to be increasing in its Generality. It is less clear that firms can always appropriate the returns to more general patents, which is what matters to banks and innovators in our framework (Hall, Jaffe, and Trajtenberg, 2005). Therefore, whether deregulation's effects vary by Generality is an interesting empirical question.

Finally as one other measure of returns, we consider the Mean Forward Citation Lag[6], which has been found to be a useful proxy for the durability of an innovation's technological contribution (Bilir 2011). It is again not obvious how well firms appropriate the returns to durability, and whether deregulation's effects vary by Mean Forward Citation Lag is an empirical question.

8.3 Estimating Impact Heterogeneity by Innovation Novelty, Complexity, and Returns

For each of the measures discussed above, we split our sample of patents based on how they score on that measure and aggregate up to the county-industry-year-type-group level, where groups are defined as low, middle, and high. Any cutoff we choose to split the groups is ultimately an arbitrary choice from a theoretical perspective, so we choose cutoffs for strong statistical and interpretative properties. Namely, we choose cutoffs to ensure each bin contains a meaningful fraction of the patents, while respecting that the distribution of characteristics may be highly skewed. For example, the distribution of Originality is not strongly skewed so we split the sample using .33 and .66 as cutoffs. On the other hand, generality is skewed left, so we split the sample using .50 and .75 as cutoffs. The data appendix contains details on how these groups are constructed. We then reestimate equation 2 on the new sample, while we include state-industry-year-group effects. The coefficients on interactions between group indicators and the treatment indicators are our estimates of the differential impact across the groups.

[5] Generality is constructed in an analogous way to Originality but using forward citations.

[6] Mean Forward Citation Lag is constructed in an analogous way to Mean Backward Citation Lag but using forward citations.

In Table 9 we show the regressions on sample splits by novelty and complexity. In column (1) we find that as expected, the effect varies by Mean Backward Citation Lag. A high Mean Backward Citation Lag means these innovations are less novel, and the effects we find are indeed concentrated there. We find no effect of deregulation on innovations with low Mean Backward Citation Lag, with mean lags below five years, which is consistent with banks viewing inventions incorporating cutting edge technologies as containing more risk. In column (2) we find that the deregulation does not vary significantly by Originality, and in fact favors relatively more original innovations. Thus, the notion of novelty that matters for lending appears to be incorporation of new technologies rather than the creation of new combinations of old technologies.

In column (3) we find that the effect of deregulation does vary by technological complexity. We find significant and substantial increases in patents with fewer than 5 claims, but significantly less effect on patents with more than 5 claims.

In Table 10, we show the regressions on sample splits by our measures of returns. In column (1) we find evidence that the effect of deregulation is concentrated among innovations in the low and middle groups of ex-post returns, with no significant effect in the high group. In column (2) we find that the effects do not vary by Generality. All Generality groups experience a boost after deregulation, with the low and high groups gaining the most. As we discussed above, imperfect appropriation of the returns to innovation could mean that even high social return projects get a boost after deregulation. In column (3), we find that the effect is strongest among innovations whose knowledge was less durable, but that there was also a significant and large increase in durable innovations.

8.4 Distribution of Gains Across Inventors

We next turn to the question of which innovators benefited the most from deregulation. Financial development should impact capital-constrained borrowers. Capital constraints may be worse in areas where borrowers have few alternatives for external finance, suggesting that the effect of deregulation may vary by the urbanization of the region. Capital constraints may also be worse for solo inventors, if one reason inventors form teams is to pool capital. Finally, capital constraints are likely to be worse for new entrants than experienced inventors with established reputations.

We split the sample by team size (solo inventor versus patents with two or more inventors), urbanization (central county with population greater than one million versus other urban counties), and inventor experience (those that appear their first time in the database, those that had one to ten patents, and those with more than ten patents), and reestimate 2 on the new sample, while we include state-industry-year-group effects[7]. We examine the capital constraints hypotheses in Table 11. In column (1) we find that the low group, noncentral counties in metropolitan areas and central counties with fewer than 1 million population, benefited the most. In column (2) we find that the impact of deregulation did not affect team invention differently from solo invention, suggesting that pooling of financial resources is not a major factor driving team invention. That team invention does not appear to be related bank deregulation rules out increasing credit constraints on invention as an alternative explanation for the increasing propensity for team invention that Jones (2009) finds. In column (3) 11, we find that the impact of deregulation is concentrated among inexperienced inventors, which is consistent with them being the most capital-constrained.

9 Discussion

We've provided evidence on the effect of a change in market structure on aggregate innovative output and its composition. We are guided by an analytical framework based on the proposition that banks do not know the riskiness of any given project, but they may believe that innovations using novel and complex technologies are riskier than others. An alternative explanation is that our patent-based metrics are simply picking up project size, so that small projects that were not profitable under monopolistic banking may become profitable under competitive banking. We believe that this explanation cannot account for all of the patterns we find. The patent-based metrics for novelty and complexity are

[7]For the team size measure, we also include type-group-year effects because there has been a secular increase in team size over our sample period that is stronger for corporate invention (Jones, 2009).

far from perfectly correlated with our measures of patent returns. (On average, the correlation is around 0.3.) Further, substantial amounts of uncertainty about the returns to an innovation are present at the time of patent filing. It therefore seems much more likely to us that banks understand that certain markets and technologies are riskier than others instead of acting based on actual ex-post returns of any given project.

Throughout the paper we have assumed taken an inventor's independent and corporate status as given. One possibility is that deregulation actually made it more likely for inventors to leave corporate employers and invent on their own. Testing this possibility directly is beyond the scope of this paper, but we do know that most of the effect we find is concentrated among new entrants into invention, which makes it less likely that the bulk of our results can be explained by this mechanism.

10 Conclusion

We find strong evidence that financial market development increases innovation. Moreover, we find that the effects are found in the subset of inventions that were less novel and less complex invented by new inventors in less urbanized counties. These suggest a channel by which financial development can shape the path of technological change and a new channel by which it affects the distribution of wealth in the long-run. Our results suggest that credit market competition can be especially effective during a stage of a country's economic development when there is a comparatively large number of well-understood technologies that have not yet been fully exploited for commercial opportunities and when the human capital necessary for innovation is dispersed geographically.

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11 Appendix: Tables and Figures

Table 1: Descriptive Statistics for Dependent Variables and Treatment Measures

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Patents	1.916	12.579	0	2388.579	440,934
Citation-weighted Patents	33.782	361.423	0	84123.477	440,934
Independent Dummy	0.500	0.500	0	1.000	440,934
Years 1-4 after reform × Independent	0.079	0.269	0	1.000	440,934
Years 5-8 after reform × Independent	0.074	0.262	0	1.000	440,934
Years 9+ after reform × Independent	0.156	0.363	0	1.000	440,934

Notes: Observations are at the county-industry-year-type level, where type distinguishes independent and corporate patents

Table 2: Description of Control Variables

Variable	Mean	Source
Population†	316,006.276	Census U.S. Intercensal County Population Data, compiled by NBER
Labor Force Composition Variables†		County Business Patterns
Employees	1,123.607	
% Establishments with Fewer than 20 Employees	0.618	
% Establishments with 20-100 Employees	0.248	
% Establishments with 100-500 Employees	0.111	
% Establishments with 500+ Employees	0.023	
County Urbanization Classification†*		USDA 1974 Rural-Urban Continuum Codes
Metro1 = 1 if fringe county of metro area with population > 1M	0.218	
Metro2 = 1 if county in metro area with population 250,000 to 1M	0.419	
Metro3 = 1 if county in metro area with population < 250,000	0.273	
Has University in 90th Percentile of Federal Research Funding†	0.171	NSF Survey of Federal Science and Engineering Support to Universities, Colleges, and Nonprofit Institutions
Post-court = 1 after 1982 for States with Below Median Favorable Patent Rulings 1953-1972	0.131	Koenig, G., 1978
State House Price Growth Rate × Indpt	0.027	FHFA Home Price Index
Unemployent Rate × Indpt	3.326	Bureau of Labor Statistics
% of State Adult Population with College Degree × Indpt	9.422	Current Population Survey
Per Capita State R&D Expenditure × Indpt	148.581	National Science Foundation's Survey of Industry Research and Development
Per Capita Personal Income	15,564.602	Bureau of Economic Analysis

†: Interactions with Independent dummy also included in regressions
∗: Omitted category is for central counties of population >1M

Table 3: Mean Annual Patenting by State

State	All	Independent (%)	Corporate (%)
CA	6888.6	28.0	72.0
NY	3499.6	22.5	77.5
TX	2689.3	20.3	79.7
NJ	2544.6	15.5	84.5
IL	2498.6	18.5	81.5
PA	2277.5	16.5	83.5
MI	2164.1	19.7	80.3
OH	2029.5	16.9	83.1
MA	1855.5	17.0	83.0
CT	1206.1	16.6	83.4
MN	1124.6	15.8	84.2
FL	1083.4	42.0	58.0
WI	725.0	16.5	83.5
WA	688.6	27.4	72.6
IN	677.9	16.1	83.9
AZ	664.1	30.2	69.8
CO	614.1	26.6	73.4
MD	591.6	35.7	64.3
NC	572.0	20.1	79.9
MO	511.4	24.7	75.3
GA	451.5	27.5	72.5
VA	397.1	35.1	64.9
OR	375.0	30.2	69.8
TN	340.2	25.6	74.4
LA	299.7	37.5	62.5
UT	269.3	31.7	68.3
OK	241.2	39.5	60.5
SC	219.6	27.2	72.8
KY	208.4	21.0	79.0
NH	177.3	17.8	82.2
IA	169.6	22.2	77.8
AL	158.6	36.0	64.0
ID	153.8	11.0	89.0
KS	132.4	34.9	65.1
RI	125.6	27.6	72.4
NV	97.9	63.0	37.0
WV	84.0	12.9	87.1
NE	80.2	42.2	57.8
NM	73.9	36.1	63.9
HI	37.5	71.7	28.3
ME	34.7	33.5	66.5
AR	31.8	44.5	55.5
MS	24.2	56.6	43.4
ND	10.1	38.9	61.1
MT	10.1	73.0	27.0

Table 4: Mean Annual Patenting by County Urbanization

Urbanization Code	**Mean Annual**	**Independent (%)**	**Corporate (%)**
Central Counties of Metropolitan Areas of 1 million population or more	15320.9	24.4	75.6
Fringe Counties of Metropolitan Areas of 1 million population or more	9231.8	21.4	78.6
Counties in Metropolitan Areas of 250,000 to 1 million population	11154.0	21.7	78.3
Central Counties of Metropolitan Areas of fewer than 250,000 population	3403.3	23.4	76.6

Table 5: Mean Annual Patenting by Manufacturing Industries

Industry (SIC2)	**Mean Annual**	**Independent (%)**	**Corporate (%)**
Industrial machinery and equipment (35)	11019.7	22.8	77.2
Electrical and electronic equipment (36)	6461.8	15.0	85.0
Instruments and related products (38)	5605.7	24.0	76.1
Chemicals and allied products (28)	5105.7	7.5	92.5
Fabricated metal products (34)	2755.8	32.2	67.8
Rubber and plastic products (30)	2526.0	28.7	71.3
Transportation equipment (37)	1225.0	38.6	61.4
Miscellaneous manufacturing (39)	1089.7	55.0	45.0
Stone, clay, glass, and concrete products (32)	561.3	26.4	73.6
Paper and allied products (26)	457.8	32.3	67.7
Primary metal industries (33)	428.4	16.5	83.5
Food and kindred products (20)	328.3	22.7	77.3
Lumber and wood products (24)	312.0	48.7	51.3
Furniture and fixtures (25)	295.9	51.2	48.8
Petroleum and coal products (29)	220.8	7.1	92.9
Textile mill products (22)	192.7	27.2	72.8
Apparel and other textiles (23)	192.2	55.6	44.4
Printing and publishing (27)	160.6	36.8	63.2
Leather and leather products (31)	145.4	56.3	43.7
Tobacco manufactures (21)	25.4	10.9	89.1

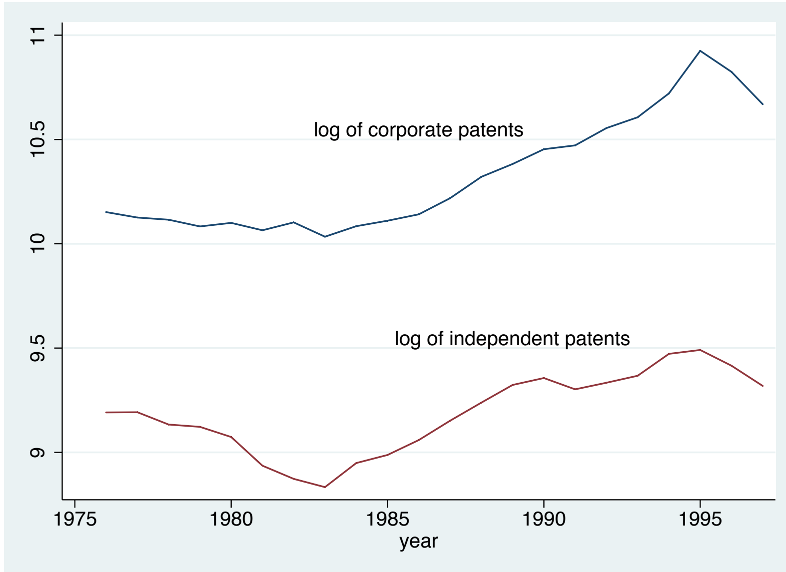

Figure 1: Patenting over time

Notes: This figure shows the log of total patents by corporate and independent inventors. The figure suggests that broad trends affect patenting activity similarly across corporate and independent inventors, although these aggregate trends may mask considerable heterogeneity across states before and after deregulation.

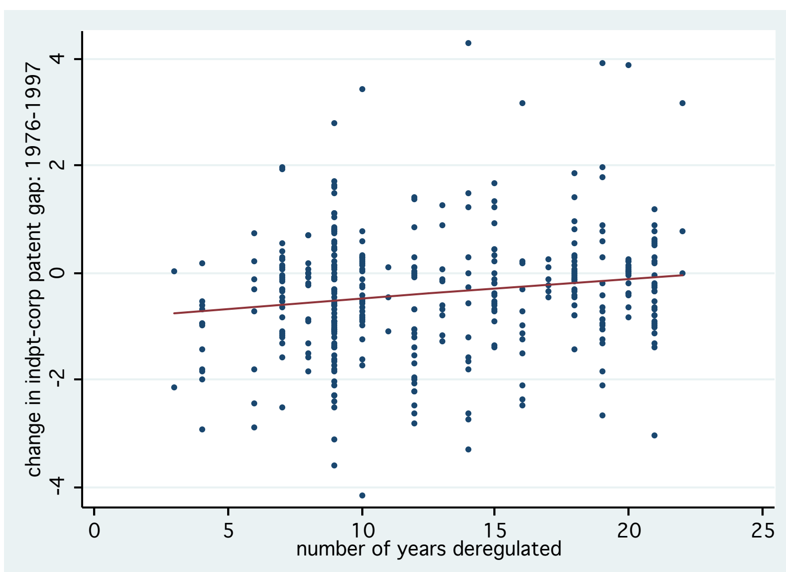

Figure 2: Years banks deregulated and Change in Independent-Corporate patenting gap by County

Notes: This figure shows the difference between 1997 and 1976 in the difference of the log of total patents by independent and corporate entities in US counties, plotted against the number of years that counties have deregulated their banks.

Table 6: Impact of Branching Deregulation on Patenting. Difference-in-Difference Estimates.

	Full Sample	**Independent Only**
Years 9+ after reform	0.703	1.164***
	(.157)	(.077)
Years 5-8 after reform	0.927	1.2225***
	(.183)	(.077)
Years 1-4 after reform	1.040	1.203***
	(.177)	(.064)
Years 0-1 before reform	1.056	1.153***
	(.121)	(.053)
Years 2-3 before reform	1.044	1.125***
	(.090)	(.040)
Years 4-5 before reform	1.052	1.073***
	(.068)	(.030)
N	411,542	205,766

Significance levels: $* \ p < .10$ $** \ p < .05$ $* * * \ p < .01$

Notes: County-industry-year observations. The dependent variable is the number of patents produced. This table presents estimates of e^{β_t}, where β_t is the treatment effect averaged across deregulated states and years within time period t. All regressions include the full set of controls. Standard errors clustered at state level and robust to misspecification of the distribution of the dependent variable shown in parentheses. See Table 2 for a detailed description of the controls.

Table 7: Impact of Branching Deregulation on Patenting.

	(1)	(2)	(3)
Years 9+ after reform	1.365***	1.296**	1.297***
	(.152)	(.130)	(.124)
Years 5-8 after reform	1.233**	1.198**	1.202**
	(.113)	(.095)	(.092)
Years 1-4 after reform	1.114	1.092	1.093
	(.091)	(.0735)	(.072)
Years 0-1 before reform	1.062	1.043	1.042
	(.055)	(.044)	(.043)
Years 2-3 before reform	1.081	1.073*	1.069
	(.055)	(.045)	(.044)
Years 4-5 before reform	1.010	1.001	.999
	(.048)	(.039)	(.038)
State-Industry-Year Effects	No	Yes	Yes
Industry-Type-Year Effects	No	No	Yes
N	411,550	411,382	411,382

Significance levels: $* \; p < .10$ $** \; p < .05$ $*** \; p < .01$

Notes: County-industry-year-type observations, where type $\in$ {independent, corporate}. The dependent variable is the number of patents produced. This table presents estimates of e^{β_t}, where β_t is the treatment effect averaged across deregulated states and years within time period t. All regressions include the full set of controls. Standard errors clustered at state level and robust to misspecification of the distribution of the dependent variable shown in parentheses. See Table 2 for a detailed description of the controls.

Table 8: Impact of Branching Deregulation on Citation-Weighted Patenting.

	(1)	**(2)**	**(3)**
Years 9+ after reform	1.383**	1.275**	1.266**
	(.193)	(.156)	(.148)
Years 4-8 after reform	1.265**	1.201**	1.196**
	(.130)	(.106)	(.102)
Years 1-4 after reform	1.117	1.070	1.067
	(.092)	(.074)	(.071)
Years 0-1 before reform	1.047	1.019	1.013
	(.066)	(.054)	(.051)
Years 2-3 before reform	1.107*	1.087*	1.075
	(.062)	(.053)	(.053)
Years 4-5 before reform	1.027	1.016	1.012
	(.053)	(.043)	(.042)
State-Industry-Year Effects	No	Yes	Yes
Industry-Type-Year Effects	No	No	Yes
N	411,550	411,382	411,382

Significance levels: $* \ p < .10$ $** \ p < .05$ $*** \ p < .01$

Notes: County-industry-year-type observations, where type $\in$ {independent, corporate}. The dependent variable is the number of citation-weighted patents produced. This table presents estimates of e^{β_t}, where β_t is the treatment effect averaged across deregulated states and years within time period t. All regressions include the full set of controls. Standard errors clustered at state level and robust to misspecification of the distribution of the dependent variable shown in parentheses. See Table 2 for a detailed description of the controls.

Table 9: Effects by Technological Novelty and Complexity

	Mean Backward Citation Lag	**Originality**	**Number of Claims**
Low Group			
Years 1-4	.982	1.059	1.139*
	(.064)	(.065)	(.081)
Years 5-8	1.034	1.112	1.275***
	(.082)	(.075)	(.092)
Years 9+	1.010	1.139	1.462***
	(.085)	(.103)	(.132)
Middle Group			
Years 1-4	1.027	1.116***	1.031
	(.036)	(.036)	(.036)
Years 5-8	1.128***	1.287***	1.132**
	(.045)	(.069)	(.053)
Years 9+	1.140**	1.381***	1.227***
	(.063)	(.074)	(.078)
High Group			
Years 1-4	1.086	1.054	1.000
	(.049)	(.041)	(.043)
Years 5-8	1.167**	1.166***	1.060
	(.061)	(.053)	(.057)
Years 9+	1.405***	1.291***	1.068
	(.089)	(.080)	(.074)
N	1,229,458	1,231,624	1,232,298

Significance levels: $* \, p < .10$ $** \, p < .05$ $*** \, p < .01$

Notes: County-industry-year-type-group observations, where type $\in$ {independent, corporate} and group $\in$ {low, middle high}. For the originality measure, the low, middle, high groups correspond to patents with below .33, between .33 and .66, and above .66 computed originality. Similarly, for the mean backward citation lag measure, patents are grouped into those below 5 years, between 5 and 20 years, and above 20 years. For the number of claims, patents are grouped into those having fewer than 5 claims, between 5 and 15 claims, and more than 15 claims. The dependent variable is the number of patents produced. This table presents estimates of e^{β_t}, where β_t is the treatment effect averaged across deregulated states and years within time period t. All regressions include the full set of controls. State-industry-year-group and industry-type effects are included in all regressions. Standard errors clustered at state level and robust to misspecification of the distribution of the dependent variable shown in parentheses. See Table 2 for a detailed description of the controls.

Table 10: Effects by Returns

	Number of Citations	**Generality**	**Mean Forward Citation Lag**
Low Group			
Years 1-4	1.079	1.081*	1.116*
	(.050)	(.049)	(.071)
Years 5-8	1.169***	1.178***	1.266***
	(.066)	(.069)	(.093)
Years 9+	1.283***	1.280***	1.375***
	(.107)	(.096)	(.123)
Middle Group			
Years 1-4	1.028	1.035	1.046
	(.050)	(.043)	(.041)
Years 5-8	1.109*	1.118*	1.142**
	(.057)	(.059)	(.054)
Years 9+	1.173**	1.158**	1.201***
	(.077)	(.070)	(.076)
High Group			
Years 1-4	.976	1.048	1.038
	(.054)	(.046)	(.061)
Years 5-8	1.144	1.147**	1.111*
	(.094)	(.054)	(.062
Years 9+	1.104	1.243***	1.228**
	(.092)	(.081)	(.084)
N	1,229,286	1,232,798	1,231,838

Significance levels: $*\ p < .10$ $**\ p < .05$ $***\ p < .01$

Notes: County-industry-year-type-group observations, where type $\in$ {independent, corporate} and group $\in$ {low, middle high}. For the number of citations measure, the low, middle, high groups correspond to patents with below the 33^{rd}, between 33^{rd} and 66^{th}, and above 66^{th} percentile number of citations. For the generality measure, patents are grouped into those below .50, between .50 and .75, and above .75 computed generality. For the mean forward citation lag, patents are grouped into those above the 25^{th}, between 25^{th} and 75^{th}, and above 75^{th} percentile lag. The dependent variable is the number of patents produced. This table presents estimates of e^{β_t}, where β_t is the treatment effect averaged across deregulated states and years within time period t. All regressions include the full set of controls. State-industry-year-group and industry-type effects are included in all regressions. Standard errors clustered at state level and robust to misspecification of the distribution of the dependent variable shown in parentheses. See Table 2 for a detailed description of the controls.

Table 11: Distribution of Gains Across Inventors

	Urbanization	**Team Size**	**Inventor Experience**
Low Group			
Years 1-4	1.121***	1.054	1.116***
	(.049)	(.044)	(.046)
Years 5-8	1.242***	1.148***	1.287***
	(.076)	(.059)	(.074)
Years 9+	1.518***	1.25***	1.354***
	(.134)	(.087)	(.099)
Middle Group			
Years 1-4			1.038
			(.039)
Years 5-8			1.094*
			(.052)
Years 9+			1.178
			(.101)
High Group			
Years 1-4	.958	1.041	.924
	(.067)	(.056)	(.116)
Years 5-8	1.024	1.129	.957
	(.068)	(.077)	(.116)
Years 9+	0.847	1.211	1.031
	(.168)	(.130)	(.145)
N	411,382	822,328	1,222,812

Significance levels: $* \; p < .10$ $** \; p < .05$ $*** \; p < .01$

Notes: County-industry-year-type-group observations for the total inventor measure, and county-industry-year-type observations for the measure of urban development, where type $\in$ {independent, corporate} and group $\in$ {low, high}. For the team size measure, the low and high groups correspond to patents only one inventor and those with more than one inventor. For the urbanization measure, the high group corresponds to central counties of metropolitan areas of 1,000,000 or more population, and the low group corresponds to all other urban counties. For the inventor experience measure, patents are grouped into those filed by new inventors, inventors with one to ten patents, and inventors with more than ten patents. The dependent variable is the number of patents produced. This table presents estimates of e^{β_t}, where β_t is the treatment effect averaged across deregulated states and years within time period t. All regressions include the full set of controls. State-industry-year-group and industry-type effects are included in all regressions where applicable. Standard errors clustered at state level and robust to misspecification of the distribution of the dependent variable shown in parentheses. See Table 2 for a detailed description of the controls.

12 Theory Appendix

12.1 The demand side: potential borrowers

We develop here a simple model to analyze the theoretical effect of deregulation on innovation. We contrast the monopoly equilibrium with the competitive equilibrium and ask whether increased competition affects the number of total patents produced and if this effect varies across different kinds of patents. Consider a firm with a project requiring initial outlay of \$1 that would yield a return $X \in \{R, 0\}$, where $X = R$ with probability $p \in [0, 1]$. Borrowers have no wealth. Borrowers may be one of two types $i = s, r$ where s stands for "safe" and r stands for "risky". Borrowers know their type but banks do not. Instead, they know the proportion of "safe" borrowers is β and of "risky borrowers" $1 - \beta$.

Assume that all projects yield the same expected returns so that $p_i R_i = m > 1 \ \forall i$, but $p_s > p_r$ and $R_s < R_r$. Banks are restricted to offering a very simple debt contract specifying a fixed repayment D in exchange for the initial outlay of \$1.

Firms have limited liability so that if $X = 0$ then firms do not repay the loan. If instead $X = R$ assume that banks can repossess the repayment amount D at some fixed cost to the firm. Thus, when $X = R$ the firm will repay the loan. In other words, the firm repays the loan if and only if $X = R$ and $R \geq D$.

Assume for simplicity there is an excess demand for funds: there is a total amount α of funds strictly smaller than the mass of borrowers.

12.2 The supply side: banks

We will compare loan outcomes under two credit market structures: monopoly and perfect competition. The monopolist sets D to maximize expected profits, subject to borrowers individual rationality. The competitive bank sets D to break even.

12.3 Equilibrium

Borrowers of type i apply for loans if and only if $D \leq R_i$.

Next consider the bank problem. If the bank is a monopolist it may set $D > R_s$ and only risky borrowers will apply. In this case the bank optimally sets $D = R_r$ and the bank earns $(1-\beta)(p_r R_r - 1)$.

If the monopolist sets $D \leq R_s$ then both borrowers will apply. In this case the bank optimally sets $D = R_s$ and earns $\alpha[(1-\beta)(p_r R_s - 1) + \beta(p_s R_s - 1)]$.

Which strategy is profit-maximizing depends on parameter values; *ceteris paribus* higher β increases the profitability of setting $D = R_s$; there will be credit rationing in this case. The monopolist will instead set $D = R_r$ if and only if

$$(1-\beta)(m-1) \leq \alpha[\beta(m-1) + (1-\beta)(p_r R_s - 1)]$$

The monopolist switches to serving only risky borrowers when β falls below β^m, defined by

$$\beta^m = \frac{(m-1) + \alpha(1 - p_r R_s)}{(m-1) + \alpha(m - p_r R_s)}$$

Next consider the competitive bank's problem. The competitive bank sets D to break even in equilibrium. If the monopolist found it optimal to set $D^m \leq R_s$ then there will still be credit rationing in competition and no change in the amount of loans funded.

If instead $D^m > R_s$ and the monopolist makes strictly positive profit, in equilibrium the competitive bank sets $D^c < D^m$. Now, it is possible for $D^c > R_s$ so that safe projects are not served in equilibrium, even when safe projects are socially efficient. This will be the case if

$$[(1-\beta)(p_r R_s - 1) + \beta(p_s R_s - 1)] < 0$$

,which is the case when the fraction of safe borrowers β is sufficiently small. This is because then the competitive bank cannot break even by charging R_s to all borrowers since the losses incurred by risky borrowers will outweigh the additional revenue from making loans to safe borrowers.

The competitive bank can break even serving both customers when

$$(1-\beta)(p_r R_s - 1) + \beta(p_s R_s - 1) \geq 0$$

If $p_r R_s > 1$ then the competitive bank can always break even serving both borrower types. In this case, safe borrowers always get served in the competitive equilibrium. If $p_r R_s < 1$ then competitive banks serve both types when β is greater than

$$\beta^c = \frac{1 - p_r R_s}{m - p_r R_s}$$

To examine whether the competitive bank will serve both customers for more values of β, we should compare β^c with β^m.

Write $x = 1 - p_r R_s$ and $y = m - p_r R_s$. Note $x < y$. Write $z = m - 1$. Now,

$$\beta^m - \beta^c = \frac{z + \alpha x}{z + \alpha y} - \frac{x}{y} = \frac{(z + \alpha x)y - (z + \alpha y)x}{(z + \alpha y)y} = \frac{zy - zx}{(z + \alpha y)y} > 0$$

In words, the competitive bank will serve both types of borrowers for more values of β than the monopolist will, in particular there are some values of β where the monopolist serves only risky borrowers, below which the competitive bank continues to serve both borrowers. If the competitive bank does not serve safe borrowers at β, then the monopolist bank does not serve safe borrowers at β. I summarize these results in the following lemma:

Lemma 1
- *At any value of β, if borrowers of all types apply for loans under monopoly then borrowers of all types apply for loans under competition.*
- *There exists an interval (a, b), $a > 0$ and $b < 1$, such that if $\beta \in (a, b)$ then under the monopolistic credit market only risky borrowers apply for loans while under the competitive credit market both safe and risky borrowers apply for loans.*

Thus, the competitive equilibrium will sometimes feature a greater number of loans funded, in which case the outcome will be an increase will concentrated among "safe" projects funded.

Intuitively, when β is very large, there will be no change in the amount of loans funded because the monopolist funds them all to begin with. When β is sufficiently small, only risky borrowers are served under both monopoly and competition since the losses to risky borrowers will outweigh the benefit of including safe borrowers in the market. For some intermediate set of values of β, safe borrowers are priced out of the market under monopoly banking but obtain loans under competitive banking. As a result, the total number of loans funded is higher under competition and monopoly, and these additional loans are for safe projects.

12.4 Observationally Distinguishable Groups

Now consider the case when there are n observationally distinguishable groups of innovative projects.

Group j is characterized by its proportion of safe borrowers β_j. Banks know if a borrower lies in group j and knows β_j for every group. If $\beta_1 > \beta_2$, then group 1 is "safer" than group 2 since a greater proportion of its borrowers have safe projects. We have in mind that more novel or complex kinds of innovations have a greater proportion of risky projects and a lower β_j.

Continue to assume that there is excess demand for funds, although each group may possess an arbitrary measure of borrowers. However, assume that the amount of funds is sufficient to fund at least the entire measure of risky borrowers.

Lemma 2 *Order the groups in descending order with respect to their β's. Under both monopoly bank setting and competitive banking,*

- *Safe borrowers in group k apply for loans only if all safe borrowers in group $j > k$ apply for and receive loans.*

Proof. Groups only differ with respect to their β's. From the monopolist analysis in the earlier section, we know that if at β it is optimal to set $D_j > R_s$, so that only risky types apply for loans, then for all $\beta' < \beta$ it is similarly optimal to set $D_k > R_s$ for $j > k$, so that only risky types from any group $k < j$ apply for loans.

Suppose for a contradiction that for some groups j and k, $j > k$, we have $D_j = D_k = R_s$, but that some borrower from group j is credit rationed, i.e. other borrowers, including some safe ones, in group j did obtain loans. Clearly the monopolist can do better by using one of the loans offered at R_s to group k to the borrowers in group j, since the debt repayment is the same yet there is a higher probability of selecting a safe borrower, which contradicts profit maximization.

Now consider competitive banking. Again we know that if banks cannot break even at $D_j \leq R_s$ at group j then they cannot break even at $D_k \leq R_s$ for group $k < j$. Suppose for a contradiction that $D_k \leq R_s$ and some safe borrower from group k obtains loans but some borrower from group j is rationed. Then one bank lending from group k could offer a rate of R_s to group j and obtain strictly more profits than lending at group k, since group j has a larger proportion of safe borrowers and the bank was charging at most R_s to group k anyway, which contradicts the zero profit condition for competitive equilibrium.

■

The main point of the lemma is that in both monopoly and competitive banking, safe borrowers from safer groups are served before borrowers in riskier groups.

The earlier results now enable us to consider what happens to different projects after a change from monopoly banking to the competitive equilibrium.

Proposition 1 *There are cutoffs β_1 and β_2 such that a change from monopolistic to competitive equilibrium has no effect for groups with $\beta > \beta_1$, increases loans funded for $\beta \in (\beta_1, \beta_2)$ with greater percentage increases in loans to groups with higher β, and no effect or a negative effect on loans funded for groups with $\beta < \beta_2$.*

Proof. By Lemma 0, we know that there exists a range of β's sufficiently large such that the monopolist bank lends to both risky and safe borrowers. By Lemma 1, we know that the competitive bank will also serve both borrowers for the same β.

By Lemma 1 part 2, we know that there is a nonempty interval of values of β such that the monopolist bank prices safe borrowers out of the market but safe borrowers are served under competition. By Lemma 2, the safe borrowers from higher β groups in this range obtain the funds "first", and then the other groups obtain funds. The percentage increase is highest in the high β groups precisely because they are high β, i.e. a higher fraction are poised to benefit from the lower prices arising from competition.

By Lemma 1 part 2, we know that at sufficiently low values of β, safe borrowers are not served under monopolistic nor competitive markets. This implies that the change in market structure cannot be positive for very low β groups.

Because there is excess demand for funds, the change in market structure may result in a negative effect on loans for some groups. In particular, if the amount of funds exceeds the measure of the groups with $\beta > \beta_2$, then the negative effect will be on groups above β_2 but may not necessarily be monotonic in β. This is because all of these groups only serve risky borrowers anyway and banks are indifferent between these groups. If instead the amount of funds is below the measure of the groups with $\beta > \beta_2$ then all of the groups with $\beta < \beta_2$ will experience negative effects on loans (no loans relative to some loans) and groups with $\beta < \beta_2$ will be rationed, with a group being rationed only if the group with a lower β is also rationed. ■

Corollary 2 *If both safe and risky projects result in patents if successful, then total number of patents should increase.*

Proof. A shift to safer borrowers leads to higher success probabilities, leading to more projects leading to patents. ■

Corollary 3 *If citations reflect returns to innovation, the number of projects with the highest ex-post returns should not increase.*

Proof. A change in market structure leads to increases in loans only to safe borrowers. This reallocation comes at the expense of risky projects, which have higher ex-post returns. ■

Corollary 4 *If citations reflect returns to innovation, the effect of deregulation on citation-weighted patenting is ambiguous.*

Proof. As a result of the corollary above, safe borrowers obtain loans at the expense of risky borrowers. Whether this results in a net increase in citation-weighted patenting depends on the translation of returns into citations. An increase in the number of citation weighted patents means that safe projects received enough citations to outweigh the reduced number of risky but high-return projects. ■

13 Data Appendix

13.1 Data Sources

In this section we describe the construction of our dataset. We first describe how we select construct our sample and measures of a patents' returns and technological novelty and complexity, and then provide details on how we split the sample based on patent-based metrics.

13.2 Construction of sample and patent metrics

As noted above, we begin with the NBER patent database covering patents granted between 1976 and 2006. Because the NBER inventor dataset only covers patents granted before 1999, we supplement inventor location information with the Harvard Business School patent database, which covers patents granted before 2010. We use inventors' cities as the location of invention. When there are multiple inventors and some live in different cities, we use the fraction of inventors in each city to weight the count of patents. Following Black and Strahan (2002), we drop Delaware and South Dakota from our analysis due to the unique incorporation and credit card banking institutions present there. Alaska is also excluded from the analysis because their county definitions fluctuate over our sample period.

Patents are assigned to industries of manufacture using a probabilistic concordance that matches patent technology classes with industry SIC codes constructed by Brian Silverman.

Our measures of Originality, Generality, Mean Backward Citation Lag, and Mean Forward Citation Lag are computed in the way suggested by Trajtenberg, Jaffe, and Henderson (1997), where we use their truncation bias adjustment for Generality.

13.3 Construction of Sample Splits

As we discussed above, we chose cuttoffs for our sample splits for strong statistical and interpretative properties. For the Originality measure, the low, middle, high groups correspond to patents with below .33, between .33 and .66, and above .66 computed Originality. For the Mean Backward Citation Lag measure, patents are grouped into those below 5 years, between 5 and 20 years, and above 20 years. For the Number of Claims, patents are grouped into those having fewer than 5 claims, between 5 and 15 claims, and more than 15 claims.

Many patents continue to receive citations decades after their grant date, implying that there are cohort effects when counting forward citations. Therefore, for the Number of Citations measure, the low, middle, high groups correspond to patents with below the 33^{rd}, between 33^{rd} and 66^{th}, and above 66^{th} percentile number of citations within their year-cohort. For the Mean Forward Citation Lag, patents are grouped into those above the 25^{th}, between 25^{th} and 75^{th}, and above 75^{th} percentile lag within the year-cohort. For the Generality measure, patents are grouped into those below .50, between .50 and .75, and above .75 computed Generality.

The low group for team size corresponds to solo invention, and the high group corresponds to patents filed for by at least two inventors. For the urbanization measure, the high group corresponds to a central county with population greater than 1 million, and the low group corresponds to all other urban counties.

For our measure of inventor experience, we use the results from the name disambiguation algorithm in the Harvard Business School patent database to identify the number of patents in our sample filed by each inventor in each year. We consider an inventor has appears for the first time in the sample period as a new inventor. Although this method of defining new entry presents obvious problems at the very beginning of the sample, most counties deregulate at least a few years into our sample period, meaning that in practice we have sufficient variation in inventor experience around our deregulation events. The low group corresponds to new inventors, i.e. those with no patents granted in an earlier year in our sample, the middle group corresponds to those with between one and ten patents, and the high group corresponds to those with more than ten patents.