RFS Advance Access published October 23, 2016

The Real Effects of Lending Relationships on Innovative Firms and Inventor Mobility

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We study how relationship lending determines the financing of innovation. Exploiting a negative shock to relationships, we show that it reduces the number of innovative firms, especially those that depend more on relationship lending such as small, opaque firms. This credit supply shock leads to reallocation of inventors whereby young and productive inventors leave small firms and move out of geographical areas where lending relationships are hurt. Overall, our results show that credit markets affect both the level of innovation activity and the distribution of innovative human capital across the economy. (*JEL* G21, O3, J61)

Received April 11, 2013; editorial decision May 25, 2016 by Editor Andrew Karolyi.

Because skilled human capital is a key input of innovation, firms and countries have engaged in a global race for the best and brightest inventors. The resulting allocation of talent in the economy can in turn determine the pace and direction of technological change. However, precisely because innovation relies on human capital and other intangible assets, its financing is inhibited by informational friction (Hall and Lerner 2010). This raises two questions: Which type of financial system is more conducive to the financing of innovation, and how does the financial system shape the allocation of talent across the economy?

Finance can affect the "industrial organization" of innovation by fostering or impeding the entry of new innovators and the expansion of existing firms, and this effect can be heterogeneous across firm types. Heterogeneous effects with respect to firm size are particularly relevant because innovative firms interact in technology markets in a way that depends crucially on their size

We thank Andrew Karolyi (the editor), two anonymous referees, Thierry Foucault, Josh Lerner, Vicente Cunat, Juanita Gonzalez-Uribe, Justin Murfin, Daniel Paravisini, Rui Silva, David Thesmar, Antoinette Schoar and participants at the NBER Entrepreneurship Working Group Meeting, the HEC Paris Conference on Finance, Banking, Real Economy and Trade, and the Adam Smith Workshop in Corporate Finance. We acknowledge financial support from the Investissements d'Avenir Labex (ANR-11-IDEX-0003/Labex Ecodec/ANR-11-LABX-0047). Supplementary data can be found on *The Review of Financial Studies* web site.
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doi:10.1093/rfs/hhw069

(Serrano 2010; Galasso and Schankerman 2015a, 2015b). The reallocation of innovation resources, particularly of skilled labor, across firms of different sizes can thus have important implications for the pace and direction of technological change (Acemoglu et al. 2013; Akcigit and Kerr 2015).

In this paper, we focus on one central element of the financial system: banking markets. The banking literature (e.g., Rajan 1992) contrasts two organization types: relationship-based versus arm's-length. In a relationship-based system, lenders are better able to acquire subjective and abstract ("soft") information through ongoing personal interactions with borrowers. Soft information can mitigate information asymmetry, especially for small, opaque firms (Petersen and Rajan 1994) and can facilitate the financing of innovation.[1] However, as Rajan and Zingales (2003) argue, a relationship-based system may favor incumbents at the expense of newcomers, preventing the entry of innovative startups. By contrast, an arm's length system may improve an innovator's chance of securing a loan by allowing them to tap a wider circle of potential lenders and facilitating the aggregation of public, "hard" information dispersed among investors.

To disentangle these competing hypotheses, we examine how the strength of lending relationships affects the level of innovation activity and the distribution of innovative human capital across the economy. First, we analyze whether relationship lending fosters or impedes the financing of innovative projects. In particular, we explore cross-sectional effects in order to contrast the effect of relationships on opaque versus transparent firms. Our goal is to study the effects of lending relationships on both the level of innovation and its distribution across firms. Second, we investigate the implications of these cross-sectional effects on the labor market for inventors. We analyze how shocks to lending relationships lead to the reallocation of innovative human capital across firms and geographical areas. We focus on the role of firm size, and we study the dynamics of competition for talent between small credit-constrained firms and larger incumbents.

The difficulty of studying the effect of lending relationships is that they are not random. In particular, they are likely to be endogenous to firm characteristics that may be correlated with innovation activity. To overcome this problem, we use the wave of intrastate banking deregulation passed in different states in the United States from the early 1970s to the mid-1990s as a shock to relationships. By removing restrictions on bank expansion within state borders, intrastate deregulation intensified banking competition (Black and Strahan 2002; Stiroh and Strahan 2003) and increased bank size (Jayaratne and Strahan 1998). Such developments in local banking markets damage lending relationships. Indeed, Petersen and Rajan (1995) show that competition reduces banks' incentives to invest in relationships, as they are less able to reap the rewards

[1] Examples of soft information include management competence and trustworthiness, types of forthcoming investment opportunities, and trade secrets whose public disclosure would reduce a project's value.

of their investments. In addition, Stein (2002) demonstrates that large banks interact more impersonally with their borrowers because they have difficulties processing non-verifiable, soft information that cannot be easily transmitted within the hierarchy.

The staggered timing of banking deregulation across states permits a difference-in-difference identification strategy that compares innovation activity before and after each deregulation event relative to a control group of states not undergoing a regulation change. We proxy for innovation activity by counting the number of firms filing patents with the U.S. Patent and Trademark Office (USPTO). An appealing feature of USPTO data is that they cover the whole universe of patents, including those filed by small and private firms.

We find that the number of innovative firms declines after states deregulate their banking systems. Exploring the dynamic effects of deregulation, we show that there is no pre-deregulation trend and that the number of innovative firms starts to decline 3 years after deregulation, decreasing to 20% below its initial level after 10 years. Given that the average state has 180 firms that file patents in a given year, a state that deregulates its banking system loses an average of 36 innovative firms over the long run. In addition, this reduction in the number of innovators is not offset by an increase in the quality of patents. On the contrary, we show that the number of citations per patent decreases by 3% after deregulation. Interestingly, we also find that the standard deviation of the number of citations decreases, which suggests that firms engage in less risky innovative projects.

Turning to cross-sectional effects, we find that the decline in innovation is stronger for firms that are more dependent on lending relationships. Our results are based on several proxies of relationship dependence. First, we construct three variables based on the National Survey of Small Business Finances to classify industries by the strength of their relationships. We find that the decline in innovation is more pronounced in industries in which firms rely more on relationships. Second, the effect is stronger in industries that are more exposed to credit supply shocks, namely, industries that are more dependent on external finance (Rajan and Zingales 1998) and those with fewer tangible assets (Almeida and Campello 2007). Third, we show that there is a decrease in innovation for small firms but not for large firms, leading to a shift in the size distribution of innovative firms.

With this credit supply shock in hand, we turn to the consequences for the labor market of inventors. For relationship-dependent innovators, reduced access to credit can lead to the reallocation of human capital from these firms to innovative firms that are not affected by banking deregulation. We look for such reallocation effects along two dimensions: across firms within deregulating states and across states. We use the HBS inventor database to track inventors and detect when they switch employers (see, Lai, D'Amour, and Fleming 2009).

Regarding cross-firm mobility, we show that inventors working for smaller firms are more likely to leave after deregulation, and when they leave, they are more likely to switch to larger firms. Focusing on the characteristics of relocating inventors, we observe that younger inventors and more productive inventors are more likely to switch to larger employers. Further, this reallocation of labor from smaller to larger innovative firms is stronger in industries that are more dependent on lending relationships, using the same proxies for relationship dependence described previously.

Across states, we find that inventors are more likely to relocate to another state when their state of origin deregulates. Consistent with the within-state mobility results, the effect is stronger for inventors working in smaller firms and for young and productive inventors. Finally, focusing on the characteristics of the new employers of relocating inventors, we find that inventors transition to larger firms when they move to deregulated states. Overall, these patterns are consistent with a banking deregulation-induced reallocation of the innovative labor force across firms and across states, away from firms that are *a priori* more dependent on lending relationships and toward firms less dependent on relationships.

Finally, we investigate the identifying assumption behind our analysis, namely, that the timing of deregulation is exogenous to innovation activity. Kroszner and Strahan (1999) show that deregulation is not random and is related to interest group factors such as the prevalence of small banks and of small firms. We estimate a duration model to test whether deregulation is explained by potential determinants of innovation (such as the state industry mix, educational attainment,or availability of venture capital funding) or by pre-deregulation innovation trends. Apart from the political economy variables of Kroszner and Strahan (1999), no other variables significantly explained the timing of deregulation. Although omitted variable and reverse causality problems can never be fully eliminated, we view this test as reassuring.

Our paper relates to several strands of the literature. First, it connects with the literature on the real effects of lending relationships (Petersen and Rajan 1994; Berger and Udell 1995; Berger et al. 2005; Zarutskie 2006; Detragiache, Tressel, and Gupta 2008). It is closely related to Bai, Carvalho, and Phillips (2015), who show that banking deregulation leads to the reallocation of labor to more productive firms. We add to this literature by focusing on an important outcome: innovation—through which the banking sector can impact economic growth. It is instructive to contrast our results with the findings of Black and Strahan (2002); Cetorelli and Strahan (2006); Bertrand, Schoar, and Thesmar (2007) and Kerr and Nanda (2009), who find that banking deregulation fosters entry. Reconciling these results with ours requires that most new firms do not innovate, which is consistent with the results of Hurst and Pugsley (2011). Thus, it is important to distinguish between innovation and entry. In particular, this distinction explains why innovation can decrease even if total entry increases.

Second, we contribute to the literature linking bank financing and innovation (Benfratello, Schiantarelli, and Sembenelli 2008; Hellmann, Lindsey, and Puri 2008; Nanda and Nicholas 2014). Amore, Schneider, and Zaldokas (2013) focus on another episode of banking deregulation in the United States, interstate banking deregulation, which allowed banks to expand across state borders. They show that interstate deregulation enabled banks to better diversify and, thus, to increase the credit supplied to innovative firms. Cornaggia et al. (2013) exploit another episode of interstate deregulation to study the dynamics of public firms' acquisitions of small innovative targets. In contrast, we focus on the wave of *intrastate* branching deregulation, which allowed banks to expand within state borders because we want to isolate the effect of a shock to lending relationships without a change in banks' ability to diversify geographically: arguably, the benefits of diversification are much lower for within-state expansion.[2] Chava et al. (2013) consider both intrastate and interstate banking deregulation. They find, like us, that innovation decreases following intrastate deregulation. However, they argue that this effect is due to reduced competition in local banking markets. We offer and test an alternative hypothesis: deregulation stifles innovation because increasing competition damages lending relationships. First, our explanation reconciles our findings with those of previous studies that intrastate branching deregulation increases banking competition (Jayaratne and Strahan 1998; Black and Strahan 2002; Stiroh and Strahan 2003; Cetorelli and Strahan 2006). Second, to disentangle Chava et al.'s hypothesis from ours, we follow the methodology of Black and Strahan (2002) to show that the effect of deregulation operates through an increase in banking competition.

Third, we contribute to a burgeoning literature on inventor mobility (Almeida and Kogut 1999; Agrawal, Cockburn, and McHale 2006; Breschi and Lissoni 2009; Marx, Strumsky, and Fleming 2009; Moretti and Wilson 2015) and, more broadly, to the literature on the domestic and international migration of skilled human capital (Borjas, Bronars, and Trejo 1992; Boustan, Fishback, and Kantor 2010; Docquier and Rapoport 2012). Our results show that finance also determines the migration of talent.

Finally, our work is related to the literature on how innovative firms react to the economic environment depending on their size (Serrano 2010; Galasso and Schankerman 2015a, 2015b) and how the allocation of innovative labor between small and large firms determines the pace and direction of technological change (Acemoglu et al. 2013; Akcigit and Kerr 2015). We contribute to this literature by showing that changes in financing conditions lead to the reallocation of skilled labor between small and large firms.

1. Data and Empirical Strategy

1.1 Banking deregulation

Before 1970, most U.S. states had strong banking market regulations. Branching was either prohibited or strongly limited, with the exception of

[2] Among other robustness tests, we check that our results are robust to controlling for interstate deregulation.

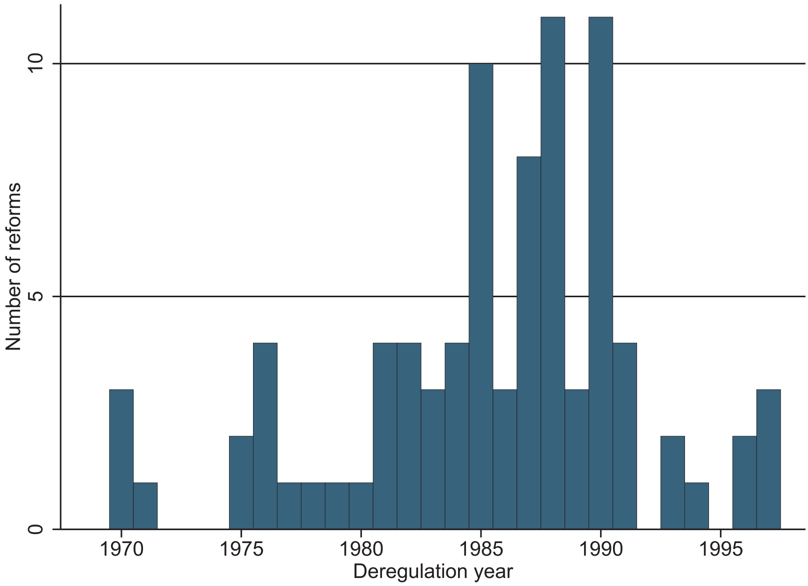

Figure 1
Timing of intrastate deregulation
This graph plots the number of reforms constituting the Black and Strahan's (2001) deregulation index that took place each year of the sample period. The reforms constituting the deregulation index are: a state allows the formation of multibank holding companies, branching by M&As, unrestricted (*de novo*) branching.

twelve states that allowed unrestricted statewide branching. Starting in 1970, all other states progressively lifted restrictions on branching within their borders. States generally relaxed restrictions on within-state bank expansion in three steps: first, by permitting the formation of multibank holding companies; then, by permitting branching by means of mergers and acquisitions (M&As) only; and finally, by permitting unrestricted (*de novo*) branching, thereby allowing banks to enter markets by opening new branches. Figure 1 illustrates the timing of deregulation in these three areas. There were 87 episodes of deregulation in 39 different states between 1970 and 1997. Because we do not have priors about which of these three steps had the greatest effect, we follow Black and Strahan (2001) and construct a deregulation index. The index equals zero if a state does not permit branching via M&As, *de novo* branching, or the formation of multibank holding companies; otherwise, the index equals the sum of the number of ways that banks may expand within a state.[3] By the end of the sample period, in 1998, 42 states had a deregulation index value equal to three.

[3] While stronger competition and larger bank size limit the ability of lenders to finance soft information-based projects, the lifting of *de novo* branching restrictions might also reduce the distance to the nearest lender, which may partially offset the loss of soft information. If this is the case, then we will underestimate the effect that hurting lending relationships will have on innovation.

In our main specification, the deregulation index enters linearly into the innovation equation, that is, we assume that increasing the index from zero (full regulation) to one has the same effect as moving from one to two or from two to three (full deregulation). We will also check that our results are robust to using the index non-parametrically.

1.2 Innovation data

1.2.1 Patents and innovative firms. 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) to measure innovation. The data contain all patents granted in the United States, along with information about the patentee (unique identifier, institutional characteristics, nationality and geographic location) and the patent (year of application, technology class and number of citations received). An appealing feature of the NBER Patents File is that it covers the entire universe of patents filed in the United States, including patents filed by young and private firms. This feature is important because these firms are more likely to be affected by changes in local banking markets, as they typically have less access to national capital markets. Comprehensive patent data are also needed to assess the effects of banking deregulation on total innovation produced in each state and to rule out explanations of our results based on changes in the shares of innovation conducted by public versus private firms.

Patents have long been used as an indicator of innovative activity (Griliches 1990); this measure, however, has disadvantages. Not all firms patent their innovations: some innovations do not meet patentability criteria, and some firms might rely on secrecy or other means to protect their innovations. In addition, patents capture only successful innovations. Despite these drawbacks, there is nevertheless a strong relationship between R&D and the number of patents observed in the cross-section of firms (R-squared is 0.9; see, Griliches 1990).

We only include patents filed by U.S. corporations in our sample, thereby excluding foreign firms, universities, and governmental agencies.[4] We date our patents according to the year in which the patent application was filed, to prevent anomalies that may arise because lags between the application and granting dates. We consider all patents filed between 1968 (2 years before the beginning of the deregulation period) and 1998 (1 year after the end of the deregulation period). Following the banking deregulation literature, we exclude Delaware. While the NBER patent data do not provide a standard industry classification, they do provide a classification based on the technology of patents. We use the two-digit classification, which includes 37 technology classes, listed in

[4] We exclude foreign firms because they often file patents with the USPTO to protect their innovations on U.S. soil but actually seek financing and perform their R&D in their home countries.

Table 1
Summary statistics: Number of innovators per industry

	Obs.	Mean	SD	25th	50th	75th
Panel A: All industries						
	57,350	5.6	13	0	1	5
Panel B: By industry						
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 peripherals	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	0.34	0.97	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

Panel A reports summary statistics on the number of innovators at the state-year-industry level across all industries. Panel B reports the same statistics by industry.

Table 1.[5] With a slight abuse of terminology, we will use the terms *technology class* and *industry* interchangeably in this paper.

The first variable of interest is the number of uniquely identified firms that file at least one patent (hereafter, "innovators" or "innovative firms") at the state-year-industry level.[6] This variable is defined for a balanced panel of 37

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

[6] To avoid double counting, when a firm files patents in several industries in a given state and year, we assign the firm to the industry(ies) in which the firm filed the largest number of patents (if the maximum is reached for several industries).

industries in 50 states (including the District of Columbia) over 31 years. Table 1 reports summary statistics for 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 substantial heterogeneity across both industries and states.

1.2.2 Inventors. The second variable of interest in our analysis is inventor mobility. The data include the names of the inventors for every patent; however, they do not provide consistent listings of inventor names or unique inventor identifiers. To overcome this problem, Lai, D'Amour, and Fleming (2009) develop a disambiguation algorithm to create unique inventor identifiers, which we use to track inventors over time.[7] Since inventor identifiers are only available starting in 1975, our analysis of inventor mobility will focus on the 1975–1998 period.

To measure inventor mobility, we follow Marx, Strumsky, and Fleming (2009) in identifying an inventor as having changed her employer if she files two successive patent applications that are assigned to different firms. Specifically, we start with the patenting histories of 630,866 unique inventors. We keep one observation per inventor-employer-year (thus dropping $n-1$ observations when the same inventor files n patents during the same year with the same employer). The unit of analysis is each pair of subsequent patents filed by each inventor. The year associated with each observation is the midpoint between the year in which the first patent is filed and the year in which the subsequent patent is filed. The final sample includes 232,091 unique inventors (inventors who appear only once are excluded) and 577,401 inventor-employer-year observations. These data allow us to detect moves when the inventor's employer differs from one patent to another. We find that 15.5% of observations are associated with a move. We define two variables to examine inventor mobility: a within-state move dummy variable that equals one if the inventor moves to a firm in the same state (13% of observations) and an out-of-state move dummy variable that equals one if the inventor moves to a firm in another state (2.5% of observations).

1.3 Baseline specification

The baseline specification is of the form:

$$E\left[Y_{jst}\right]=\alpha_j+\gamma_s+\delta_t+\beta\ Deregulation_{st}+Controls, \tag{1}$$

where Y_{jst} is the outcome variable (for instance number of innovators or inventor mobility) in industry j, state s, and year t. $Deregulation_{st}$ is the index equal to the number of steps of deregulation that have been implemented in state s up

[7] The data are available at http://dvn.iq.harvard.edu/dvn/dv/patent, and the disambiguation algorithm is discussed in Lai, D'Amour, and Fleming (2009).

to year t, that is, the index is incremented by one for all years following each deregulation event; and α_j, γ_s, and δ_t are industry, state, and year fixed effects, respectively. The parameter of interest is β. It measures the permanent effect of one step of deregulation (out of three possible steps) on the outcome variable Y. The identification of β relies on comparing Y before and after deregulation relative to a control group of states not experiencing a change in regulation.

In the analysis of the number of innovative firms, the outcome variable is the number of innovators in industry j, state s and year t. Following the innovation literature, we estimate a Poisson model to take into account the count nature of the dependent variable, that is, the right-hand side of Equation (1) is replaced by its exponent. Industry fixed effects account for heterogeneity in the propensity to innovate and to patent innovation across industries. State fixed effects capture time-invariant determinants of innovation in different states, such as the size of the state, the sectoral composition, and the level of education. Year fixed effects control for aggregate shocks and common trends in innovation activity.[8] We also control for time-varying state characteristics that may affect innovation: annual number of college degrees granted, annual number of doctorates granted, annual amount of federal funds for R&D, and volume of capital invested each year by venture capitalists.[9] The Poisson model is estimated using maximum likelihood, and standard errors are clustered at the state level to account for serial correlation and correlation within states.

In the analysis of inventor mobility, we estimate a linear probability model at the inventor level, where the outcome variable Y_{ijst} is the within-state move dummy or the out-of-state move dummy for inventor i in industry j, state s, and year t. Again, fixed effects account for heterogeneity in inventor mobility across industries, across states, and over time. We include the same time-varying state characteristics as before and the age of the inventor, defined as the number of years since she first filed a patent, as control variables.

2. Effect on Innovative Firms

2.1 Baseline tests

We start by analyzing the effects of banking deregulation on the number of innovative firms. Before reporting the results of the baseline Poisson model, we estimate the dynamic effects of deregulation around the event date. In Figure 2, we re-estimate the Poisson model, where the deregulation index is replaced by dummy variables for each year from 10 years before to 10 years after each deregulation step. Reassuringly, there is no trend before the event date. In particular, the number of innovators 10 years before deregulation

8 Such common shocks can be caused by changes in the legal and institutional environment at the federal level, such as the creation of the Court of Appeals for the Federal Circuit in 1982.

9 Data on educational attainment and federal R&D expenses come from the National Science Foundation's CASPAR database, while information on venture capital funds is from VentureXpert.

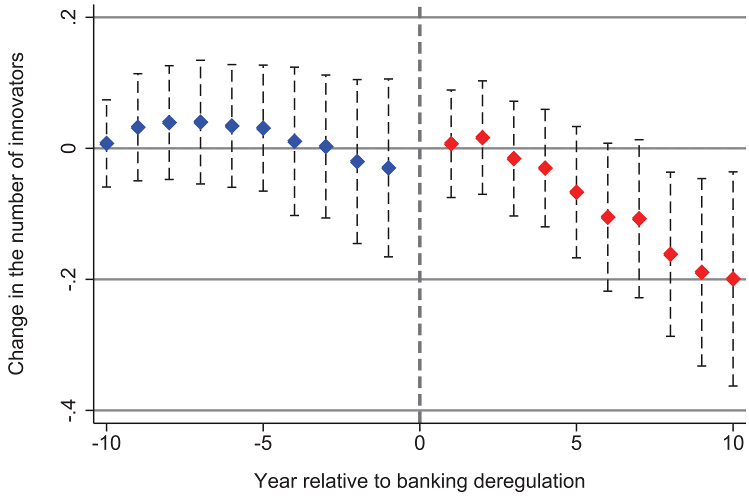

Figure 2
Effect of banking deregulation on innovation
The figure shows the evolution of innovation around deregulation dates. The specification is the same as Equation (1), except that the deregulation index is replaced by a collection of variables $\sum_{s=1}^{3} I^s(k)$, where $I^s(k)$ is a dummy equal to one exactly k years after (or before if k is negative) the state implements a given step of deregulation $s \in \{1,2,3\}$. We plot the point estimates for $k=-10,\ldots,10$, using the deregulation year $k=0$ as the reference year, as well the 95% confidence interval using standard errors clustered at the state level.

almost equals the number of innovators at the time of deregulation. This pattern is consistent with our identifying assumption that deregulation is not endogenous to innovation (more on this in Section 4). Figure 2 also shows that the effect of deregulation starts to materialize three to four years after the event. There are two possible explanations for this result. First, it can take a few years for deregulation to reshape the banking market structure and lead to the development of large banks (Jayaratne and Strahan 1998). However, the adverse effect of competition on banks' incentives to invest in lending relationships is effective as soon as banks anticipate increased competition, which is at the time of deregulation (or even before, if deregulation is anticipated). Second, there is a delay between the funding of an innovative project and the filing of a patent application by a firm.

We now turn to formal statistical tests, whose results are reported in Table 2. Column (1) shows that every deregulation step leads to a statistically significant 10% decline in the number of innovators.[10] In Column (2), we add time-varying control variables for the level of education, federal R&D spending, and venture capital activity at the state level. All these variables are significant with the

[10] We interpret coefficients in the Poisson model as semi-elasticities by doing a first-order Taylor approximation. The exact interpretation of the coefficient −0.100 is that every step of deregulation leads to an average percentage change in the number of innovators by $e^{-0.100}-1=-10.5\%$. In order to streamline the exposition of the results, we stick to the first-order approximation and interpret coefficients as semi-elasticities.

Table 2
Number of innovators: Effect of banking deregulation

	Poisson model: Number of innovators				OLS: Average citations per patent	OLS: Median citations per patent	OLS: SD citations per patent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deregulation	−0.100***	−0.073**			−0.033***	−0.035***	−0.029**
	(0.035)	(0.036)			(0.0094)	(0.0087)	(0.012)
Index = 1			−0.12*				
			(0.07)				
Index = 2			−0.19**				
			(0.079)				
Index = 3			−0.26**				
			(0.1)				
Deregulation ($\leq t-5$)				0.029			
				(0.035)			
Deregulation ($t-4; t-1$)				−0.012			
				(0.019)			
Deregulation ($t+1; t+4$)				−0.031***			
				(0.0099)			
Deregulation ($\geq t+5$)				−0.10***			
				(0.026)			
College graduates		0.51***	0.32	0.36*	0.04	0.019	0.078
		(0.2)	(0.23)	(0.21)	(0.063)	(0.067)	(0.078)
PhD graduates		0.43**	0.52***	0.44***	0.033	0.031	0.061
		(0.18)	(0.2)	(0.17)	(0.05)	(0.053)	(0.066)
R&D federal expenses		0.044	0.0082	0.015	0.0073	0.0033	−0.0035
		(0.042)	(0.053)	(0.05)	(0.014)	(0.014)	(0.019)
VC funds		0.026**	0.00028	0.0079	0.0058	0.00076	0.016
		(0.013)	(0.017)	(0.016)	(0.0083)	(0.008)	(0.01)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,350	57,350	57,350	57,350	23,024	23,024	23,024
Pseudo-R2/Adjusted-R2	0.73	0.73	0.73	0.73	0.44	0.53	0.57

Note: 50 U.S. states, 37 industries, from 1968–1998. In Columns (1) to (3) we estimate a Poisson model in which the dependent variable is the number of innovators at the state-industry-year level. In Column (1) the only explanatory variable is the deregulation index which ranges from zero (full regulation) to three (full deregulation). In Column (2) we control for the state-year-level numbers of college degrees granted, doctorates granted, amount of federal R&D spending, and dollar amount of invested VC capital. In Column (3) we use dummy variables for each value of the deregulation index and estimate the effect of the deregulation non parametrically. In Column (4) we split the deregulation index into 4 sub-periods: more than 4 years before deregulation, the 4 years preceding deregulation, the 4 years following deregulation, and more than 4 years after deregulation. In Columns (5) to (7), we estimate linear regression models in which the dependent variable is defined in all state-industry-year cells with at least one innovator. In Column (5) the dependent variable is the average number of citations per patents; in Column (6), it is the median number of citations per patents; in Column (7), it is the standard deviation of the number of citations per patents. All regressions include state, year, and industry fixed effects. Standard errors are clustered at the state level.

expected sign, except federal R&D spending, which is insignificant; this may be because federal spending is directed toward moderately innovative states. The coefficient on the deregulation index remains negative at −7.3% and significant at the 5% level. Given that the deregulation index ranges from zero to three, it indicates that the number of innovators decreases by slightly more than 20% when a state moves from being fully regulated (deregulation index equal to zero) to being fully deregulated (deregulation index equal to three).

One issue is whether a linear specification of the index is appropriate. To check this, we replace the deregulation index with dummy variables for each level of the index between one and three (with zero being the reference group) and estimate the effect non-parametrically. Column (3) indicates that the effect is monotonic in the intensity of deregulation: an index of one significantly reduces the number of innovators by 12%, an index of two by 19%, and an index of three by 26%. Although the effect is not perfectly linear, the linear specification seems a reasonable approximation.

In Column (4), we exploit the time dimension of the panel more fully 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 with 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 periods around each step of deregulation. The deregulation year is the reference year. First, as seen in Figure 2, we find that there is no pre-deregulation trend. Second, it takes some time before the effects of deregulation materialize: the number of innovators decreases by 3.1% in the first 4 years after deregulation, and it subsequently decreases by 10%.

Next, we investigate whether the decrease in the quantity of innovation is offset by an increase in the quality of innovation or by a shift toward more risky innovative projects. We measure patent quality as the average (or median) number of citations per patent, which is a standard measure of patent quality (Hall, Jaffe, and Trajtenberg 2005).[11] To measure innovation riskiness, we posit that risky innovative projects are more likely to lead either to valuable and highly cited patents or to low-quality patents with a low number of citations. Accordingly, we measure innovation riskiness as the standard deviation of the number of citations per patent. Columns (5) and (6) show that the average (median) number of citations declines by 3.3% (3.5%). Therefore, the reduction in the quantity of innovation is not offset by an increase in the quality of innovation. Instead, innovation shifts toward less ambitious, more incremental projects, which might be easier for creditors to evaluate but are less valuable. The effect on the riskiness of innovation presents a similar pattern. Column (7) shows that the standard deviation of the number of citations per patent decreases by 2.9%, indicating that firms engage in less risky innovative projects. If one envisions the investment opportunity set as exhibiting a risk-return tradeoff, deregulation leads to a shift toward projects with lower potential and lower risk.

[11] Citation truncation is not a major concern because the sample period ends in 1998, and we have citations up to 2006. In addition, year fixed effects control for any truncation bias that is constant across all patents in the same cohort.

2.2 Cross-sectional tests

In this section, we conduct cross-sectional tests of the hypothesis that innovation declines because lending relationships are damaged by deregulation. Specifically, we test whether the negative effect of deregulation is stronger in industries that are *a priori* more dependent on lending relationships or more sensitive to credit supply shocks.

First, we test whether innovative firms in relationship-dependent industries are more affected by deregulation. We create three industry-level proxies of relationship dependence using the National Survey of Small Business Finances (1987 and 1998), which provides thorough documentation of firms' relationships with financial institutions.[12] The first proxy 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), when the distance between the bank lending office and the borrowing firm is greater, they communicate in more impersonal ways and are less able to share soft information. The second proxy is drawn from Landier, Nair, and Wulf (2009) and is defined as the average increase in distance between banks and borrowers 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. The third proxy for relationship dependence is the average length of the relationship between banks and borrowers in 1987 (Petersen and Rajan 1994). Low correlations between these measures suggest that they capture different dimensions of relationship dependence.[13] Finally, we map each of the three variables onto the 37 patent classes that we use in our regressions and classify a patent class as relationship dependent if the variable is above the sample median.[14]

In Table 3, Columns (1)–(3), we regress the number of innovators on the deregulation index and its interaction with each of the three measures of relationship dependence, as well as on the previous set of controls and fixed effects. For all three measures, the negative effect of deregulation is stronger in more relationship-dependent industries, while the effect is never significant in industries that are less reliant on relationships (the reference group in the regression). The difference between high and low relationship-dependent industries is −3.8% when relationships are proxied by the average distance from the lender, −2.9% when relationships are proxied by the change in distance,

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[12] For more details about this database, see Petersen and Rajan (2002). We provide more detail on how we construct these proxies in Appendix A.

[13] The correlation between (minus) 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. The first correlation is negative because that distance is measured in 1987 and is computed between 1987 and 1998, and it is easier to increase the distance when the initial distance is small.

[14] We obtain similar results if we split industries into terciles or quartiles of relationship dependence and if we use the continuous variables.

Table 3
Number of innovators: Relationship dependence and sensitivity to credit supply

	Poisson model: Number of innovators				
	Industry proxy for relationship dependence:				
	Distance with lender	Increase in distance with lender	Length of relationship with lender		
	(1)	(2)	(3)	(4)	(5)
Deregulation	−0.055	−0.06	−0.027	−0.015	−0.022
	(0.035)	(0.039)	(0.025)	(0.02)	(0.024)
Deregulation × relationship dependence	−0.038***	−0.029***	−0.091***		
	(0.012)	(0.01)	(0.025)		
Deregulation × external finance dependence				−0.076***	
				(0.021)	
Deregulation × low asset tangibility					−0.06***
					(0.013)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	57,350	57,350	57,350	57,350	57,350
Pseudo-R2	0.74	0.74	0.74	0.76	0.75

Note: 50 U.S. states, 37 industries, from 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 the deregulation index, state, year, and industry fixed effects, and the same set of state-year control variables as in Table 2. In Columns (1) to (3), we include an industry-level dummy for high relationship dependence and its interaction with the deregulation index, with the state and year fixed effects, and with the control variables. (We only report the coefficient on the interaction with the deregulation index.) In Columns (1) relationship dependence is measured as (minus) average distance from main lender; in Column (2), it is measured as (minus) average change in distance from main lender; in Column (3), it is measured as average length of relationship with main lender. In Column (4), we replace relationship dependence by the dummy for high external finance dependence. In Column (5), we replace it by the dummy for low asset tangibility. Standard errors are clustered at the state level.

and −9.1% when proxied by the length of relationships; the results for all three proxies are significant at the 1% level.

Second, to provide further evidence that our findings are explained by credit supply shocks, we test whether the effect is stronger for firms that are more sensitive to such credit supply shocks. We consider two standard measures of sensitivity to credit supply shocks. The first is Rajan and Zingales's (1998) measure of external finance dependence, defined as the industry average of the fraction of investment that cannot be financed by current cash flows. The second proxy for sensitivity to financing frictions is asset tangibility (Almeida and Campello 2007). Berger and Udell (1995) show that banks ask for more collateral when they have weaker relationships with borrowers. Accordingly, we expect firms with fewer tangible assets to be more affected by deregulation. We measure asset tangibility as the industry average of the ratio of net property, plant, and equipment over total assets. We construct these two variables using Compustat and map the SIC onto patent classes. An industry is considered more sensitive to credit supply shocks when its measure of external finance dependence is above the median and when asset tangibility is below the median.

Table 4
Intensive margin

	OLS: Average number of patents per innovator	Poisson model: Total number of patents by all innovators	Poisson model: Total number of patents by small innovators	Poisson model: Total number of patents by large innovators
	(1)	(2)	(3)	(4)
Deregulation	0.033	−0.051**	−0.085***	−0.038
	(0.023)	(0.025)	(0.024)	(0.095)
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	23,024	57,350	57,350	57,350
Adjusted-R2/Pseudo-R2	0.19	0.69	0.69	0.61

Note: 50 U.S. states, 37 industries, from 1968–1998. In Column (1) we estimate a linear regression model in which the dependent variable is the average number of patents per innovator, which is defined for state-industry-year cells with at least one innovator. In Columns (2) to (4) we estimate Poisson models. In Column (2), the dependent variable is the total number of patents filed by all innovators at the state-industry-year level; in Column (3), it is the total number of patents filed by innovators with a number of patents below the industry-year median; in Column (4), it is the total number of patents filed by innovators with a number of patents above industry-year median. All the specifications include the deregulation index, state, year, and industry fixed effects, and the same set of state-year control variables as in Table 2. Standard errors are clustered at the state level.*Ordinary Least Square (OLS).

In Column (4) of Table 3, the interaction term between deregulation and financial dependence is negative and statistically significant. Therefore, industries that are more reliant on external financing are more affected by deregulation. In contrast, there is no significant effect on industries with low external dependence (the reference group in the regression). This is consistent with the interpretation that the observed drop in innovation is due to a credit supply shock. A similar picture emerges in Column (5) when we use asset tangibility as a proxy for sensitivity to credit supply shocks: low-asset-tangibility industries are most affected by deregulation, whereas the effect is dampened for industries with more tangible assets.

2.3 Intensive margin and firm size

Thus far, we have focused on the number of innovators, that is, on the extensive margin of the population of innovative firms. We now turn our attention to the effect of deregulation at the intensive margin, that is, on the number of patents per firm.

In Column (1) of Table 4, we estimate a linear regression model where the left-hand side variable is the log of the average number of patents per innovator at the state-industry-year level. The coefficient on deregulation is positive and indicates that the average number of patents per innovator increases by 3.3%, although the coefficient is not statistically significant at conventional levels (p-value of 0.15). Given that the number of innovators decreases by 7.3% (see, Table 2, Column [2]), we expect the total number of patents to decrease by approximately 4%. To confirm this back-of-the-envelop calculation, we estimate a Poisson model for the total patent count in Column (2). The total number of patents decreases by 5.1%, a change that is significant at the 5% level. Consistent with the slight increase in the number of patents per innovator, the total number of patents decreases by less than the number of innovators.

The increase in the average size of innovative firms has two non-mutually exclusive interpretations. First, it can reflect a composition effect by which small innovators drop out and only large innovators remain. This interpretation is consistent with the hypothesis that the deregulation of local banking markets affects small firms, whereas large firms that have access to national capital markets are less affected. Second, innovators may endogenously become larger to match the larger size of banks following deregulation.

To disentangle these two effects, we test whether large innovators become even larger. We proxy for size using the number of patents filed by a firm in a given year and define large innovators as those with patents above median number for a given industry-year and small innovators as those below median. We compute the sample median by industry-year because patenting intensity varies across industries and over time. Importantly, the industry-year median is not state specific because the size distribution in each state is precisely the dependent variable we analyze. We then decompose the total patent count into patents filed by small innovators and by large innovators. Consistent with our previous results, in Column (3), the number of patents filed by small innovators decreases by 8.5%, which is significant at the 1% level. In contrast, in Column (4), there is no significant effect on the number of patents filed by large innovators. Hence, the decrease in the number of small innovators is not offset by more patenting among large innovators.

The evidence is thus more consistent with the first interpretation: the number of small innovators shrinks because they are hurt by deregulation, whereas large innovators are not. This finding indicates a shift in innovation from small firms to larger firms. In the next section, we explore this issue in more depth by studying reallocation on the labor market for inventors, particularly between small and large firms.

3. Labor Market Reallocation

In this section, we investigate the effect of credit supply shocks produced by deregulation on the labor market for inventors. We test whether small innovative firms that experience tightening of bank credit lose their inventors to larger firms after deregulation . We use the inventor-level data described in Section 1.2.2, which track inventors over time and across the firms for which they file patents. The unit of analysis is each pair of subsequent patents filed by an inventor, where an observation can correspond to an inventor filing both patents for the same firm (no move), an inventor filing both patents for two different firms in the same state (within-state move), or an inventor filing both patents for two different firms in two different states (out-of-state move).

Table 5
Inventor mobility within state

	Within state move dummy *(All inventors)*	New employer size/ previous employer size *(Only moving inventors)*			
	(1)	(2)	(3)	(4)	(5)
Deregulation	0.013	0.078**	0.024	0.055	0.065**
	(0.0088)	(0.032)	(0.03)	(0.035)	(0.031)
Deregulation × small previous employer	0.026***				
	(0.0076)				
Deregulation × young inventor			0.038**		
			(0.016)		
Deregulation × forward-looking productive inventor				0.054***	
				(0.017)	
Deregulation × backward-looking productive inventor					0.034***
					(0.0092)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	577,401	75,962	75,962	75,962	75,962
Adjusted-R2	0.081	0.25	0.25	0.25	0.25

Inventor data were compiled by Lai, D'Amour, and Fleming (2009), from 1975–1998. We estimate linear regression models at the inventor-year level. All regressions include state, year, and industry fixed effects, the same set of state-year control variables as in Table 2, and inventor age. In Column (1) the dependent variable is a dummy variable equal to one if the inventor moves to another employer in the same state as her previous employer. The explanatory variables include the deregulation index, a small previous employer dummy equal to one if the initial employer size (defined as the number of employed inventors in the initial year) is below median size, and the small previous employer dummy interacted with the deregulation index, with the state and year fixed effects. We only report the coefficient on the interaction with the deregulation index. In Columns (2) to (5), we restrict the sample to observations corresponding to a move to another firm in the same state. The dependent variable is the ratio of new employer size over previous employer size. In Column (2) the explanatory variables include the deregulation index and the same set of controls and fixed effects as before. In Column (3) we add a young inventor dummy (equal to one if inventor age is below median) and its interaction with the deregulation index, with the state and year fixed effects and with the controls. In Column (4) we replace the young inventor dummy by the forward-looking productive inventor dummy equal to one if her forward number of patents is above industry-year median; and in Column (5), by the backward-looking productive inventor dummy equal to one if her backward number of patents per year is above industry-year median. Standard errors are clustered at the state level.

3.1 Within-state inventor mobility

We start by analyzing within-state inventor mobility. We regress the within-state move dummy on the deregulation index and its interaction with a dummy variable that equals one if the inventor's initial employer is below the median size, where firm size is defined as the number of inventors at the firm-year level. We include the same set of fixed effects and time-varying state characteristics, as well as inventor age, as controls.

In Column (1) of Table 5, we find that the likelihood that an inventor leaves a small employer increases by 3.9 percentage points (0.013+0.026) after each step of deregulation. This corresponds to a 30% increase relative to the unconditional probability of moving. In contrast, there is no significant effect on mobility away from large firms (the reference group in the regression). To check that our results are not driven by trends in inventor mobility, we conduct a graphical analysis of the dynamic effect of deregulation. To do so, we follow

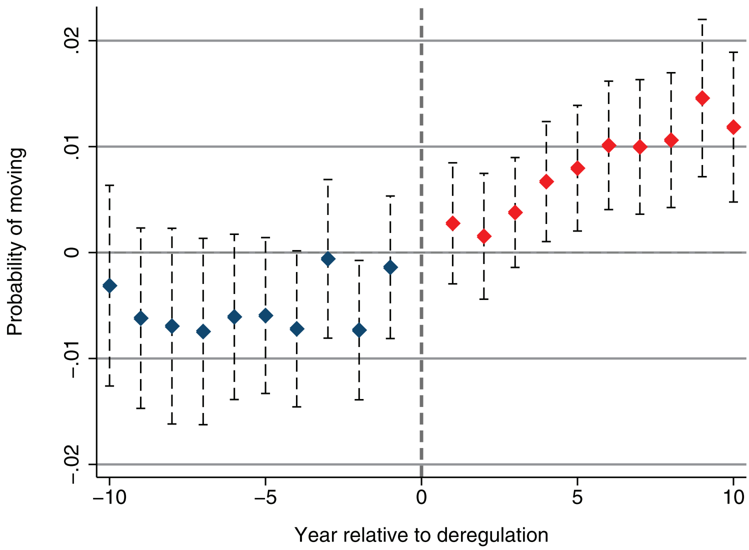

Figure 3
Within-state inventor mobility around deregulation events
The figure shows the evolution of within-state inventor mobility around deregulation dates. The specification is the same as in the first column of Table 5, except that the deregulation index is replaced by a collection of variables $\sum_{s=1}^{3} I^s(k)$, where $I^s(k)$ is a dummy equal to one exactly k years after (or before if k is negative) the state implements a given step of deregulation $s \in \{1,2,3\}$. We report the coefficients on the interaction term with the small previous employer dummy for $k=-10,\dots,10$, using the deregulation year $k=0$ as the reference year, as well the 95% confidence interval using standard errors clustered at the state level.

the same method used to create Figure 2: we replace the deregulation index with dummy variables for each year from 10 years before to 10 years after each deregulation step and plot the coefficients of the interaction terms with the small employer dummy in Figure 3. The figure shows no pre-deregulation trend, and the effect of deregulation progressively materializes a few years after deregulation. This result closely mirrors the pattern in Figure 2.

We next investigate whether moving inventors leave small firms to work for larger firms. We focus on the subsample of inventor-employer-year observations corresponding to a change of employer within the state and compute the ratio of new employer size to previous employer size. Column (2) in Table 5 shows that after deregulation, the ratio of new employer size to previous employer size increases by a significant 7.8 percentage points. That is, conditional on switching to another employer in the same state, inventors move, on average, to larger firms after deregulation.

Then, we focus on the characteristics of inventors who move from small to large firms using three variables. The first is inventor age, which we measure as the time elapsed since the inventor first filed a patent. We define young inventors as those below the median inventor age. Then, we aim to capture talented inventors. The second variable is the number of patents the inventor will file in the future. We define (forward-looking) productive inventors as those with a number of future patents above the industry-year median. A potential concern with forward productivity is that it may be endogenous to mobility. For instance, if inventors leave deregulated states to work for less credit-constrained employers, this may make them more productive. To overcome this possible bias, we construct a third variable based on backward-looking productivity. We count the number of patents the inventor filed in the past divided by the number of years since the first patent. We define (backward-looking) productive inventors as those with a number of previous patents per year above the industry-year median. We interact the deregulation index with each of these three inventor characteristics.

Column (3) in Table 5 shows that the coefficient on the interaction between deregulation and the young inventor dummy is positive and significant. Therefore, after deregulation, young inventors are more likely to move to larger employers compared with older inventors. Column (4) shows that the new employer to previous employer size ratio also increases more for productive inventors based on the forward-looking measure. In Column (5), the result is similar using the backward-looking measure of productivity. Hence, the shift of inventors toward larger firms is more pronounced for young and talented inventors, who may be more mobile and in stronger demand than other inventors.

Next, we examine whether inventor reallocation depends on the type of industry. Our main result is that inventors move from more to less relationship-dependent firms. This pattern can materialize along two dimensions: within and across industries. Within industries, the hypothesis is that small firms are more relationship dependent. Thus, we test whether reallocation from small to large firms is more pronounced in industries that are more reliant on relationships using the same set of proxies for exposure to deregulation constructed in Section 2.2: distance with lender, increase in distance with lender, length of relationship, external finance dependence, and low asset tangibility. For each proxy, we re-estimate the specification used in Column (1) of Table 5, where we interact all the right-hand-side variables with industry relationship dependence. The results are reported in Table 6. The coefficient on the triple interaction among deregulation, small previous employer, and relationship dependence is positive using all proxies, and four of five are statistically significant at conventional levels. Thus, inventor reallocation from small to large firms is more pronounced in industries in which small firms are more affected by deregulation.

Finally, we test whether inventors switch industries following deregulation and move from more to less relationship-dependent industries. Remember that we define industries as patent technology classes. Thus, switching industries may be difficult for inventors if human capital is specific to a technology class. We test this hypothesis following the same methodology used in Column (2) of Table 5: we focus on the subsample of inventors moving within state,

Table 6
Inventor mobility within state: Relationship dependent industries

	Within-state move dummy				
	Industry proxy for relationship dependence:				
	Distance with lender	Increase in distance with lender	Length of relationship with lender	External finance dependence	Low asset tangibility
	(1)	(2)	(3)	(4)	(5)
Deregulation × small previous employer × relationship dependence	0.018*	0.019**	0.027***	0.015*	0.0086
	(0.0098)	(0.009)	(0.0099)	(0.0079)	(0.01)
Deregulation	0.046***	0.046***	0.053***	0.081***	0.049***
	(0.0074)	(0.0069)	(0.007)	(0.014)	(0.008)
Deregulation × small previous employer	0.021***	0.02***	0.017***	0.0045	0.024***
	(0.0064)	(0.0053)	(0.0063)	(0.015)	(0.0081)
Deregulation × relationship dependence	−0.0091	−0.0092	−0.024***	−0.026***	−0.011
	(0.0071)	(0.0071)	(0.0083)	(0.0062)	(0.0078)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	577,400	577,400	577,400	577,400	577,400
Adjusted-R2	0.14	0.13	0.14	0.14	0.13

Inventor data were compiled by Lai, D'Amour, and Fleming (2009), from 1975–1998. We estimate linear regression models at the inventor-year level where the dependent variable is a dummy variable equal to one if the inventor moves to another employer in the same state as her previous employer. The explanatory variables include the deregulation index, a small previous employer dummy equal to one if the initial employer size (defined as the number of employed inventors in the initial year) is below median size, an industry-level proxy relationship dependence, and the interactions between these three variables. We only report the coefficient on the interactions with the deregulation index. In Column (1) the relationship dependence proxy is defined using (minus) average distance from main lender; in Column (2), using (minus) average change in distance from main lender; in Column (3), using average length of relationship with main lender; in Column (4), using external finance dependence; and in Column (5), using low asset tangibility. Standard errors are clustered at the state level.

and we regress the ratio of the relationship dependence of the previous employer's industry to that of the new employer. These results are relegated to Online Appendix 0.1 for the sake of space. We find only weak evidence of inter-industry mobility from more to less dependent industries. The effect is significant for only two of five proxies for relationship dependence, suggesting that inventor mobility occurs mostly within industries.

3.2 Out-of-state inventor mobility

The labor force may also be reallocated across geographical areas. In Table 7, we investigate whether inventors leave states that deregulate. In Column (1), we regress the out-of-state move dummy on the deregulation index and find a positive and significant coefficient. The likelihood that an inventor leaves the state increases by 0.95 percentage points following each step of deregulation. This corresponds to a 35% increase relative to the unconditional probability of the inventor leaving the state. To check that this result is not confounded by trends in inventor mobility across states, we perform a graphical analysis of the dynamic effect of deregulation on out-of-state inventor mobility. Figure 4 shows that there is no pre-deregulation trend and that out-of-state inventor

Table 7
Inventor mobility out of state

	Out-of-state move dummy				
	(1)	(2)	(3)	(4)	(5)
Deregulation	0.0095***	0.0066**	0.013***	0.014***	0.015***
	(0.0031)	(0.0028)	(0.0023)	(0.0025)	(0.0025)
Deregulation × small previous employer		0.0056***	0.0044*	0.0049**	0.0054**
		(0.0018)	(0.0025)	(0.0021)	(0.0025)
Deregulation × young inventor			0.0042***		
			(0.0012)		
Deregulation × small previous employer × young inventor			0.003*		
			(0.0018)		
Deregulation × forward-looking productive inventor				0.0048***	
				(0.0014)	
Deregulation × small previous employer × forward-looking productive inventor				0.0058**	
				(0.0026)	
Deregulation × backward-looking productive inventor					0.0021
					(0.0018)
Deregulation × small previous employer × backward-looking productive inventor					0.0046**
					(0.0021)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	577,400	577,400	577,400	577,400	577,400
Adjusted-R2	0.026	0.028	0.012	0.013	0.012

Inventor data were compiled by Lai, D'Amour, and Fleming (2009), from 1975–1998. We estimate linear regression models at the inventor-year level. In all regressions the dependent variable is a dummy variable equal to one if the inventor moves to another employer located in a different state than her previous employer. All regressions include state, year, and industry fixed effects, the same set of state-year control variables as in Table 2, and inventor age. In Column (1) the explanatory variable of interest is the deregulation index. In Column (2) we add a small previous employer dummy equal to one if initial employer size (defined as the number of employed inventors in the current year) is below median size and its interaction with the deregulation index, with the state and year fixed effects (we only report the coefficient on the interaction with the deregulation index). In Column (3) we add a young inventor dummy equal to one if inventor age is below median and its interaction with all the explanatory variables in Column 2 We report only the coefficients on the interactions with deregulation. In Column (4) we replace the young inventor dummy by the forward-looking productive inventor dummy equal to one if her forward number of patents is above industry-year median; and in Column (5), by the backward-looking productive inventor dummy equal to one if her backward number of patents per year is above industry-year median. Standard errors are clustered at the state level.

mobility increases progressively after deregulation, which mirrors the pattern in Figures 2 and 3.

We then study the heterogeneity of this effect across firms and inventors. In Column (2) of Table 7, we interact the deregulation index with the small firm dummy and find that the interaction term is positive and significant. Therefore, inventors are more likely to leave states that deregulate when they initially work for a small firm, which is consistent with the hypothesis that small firms are disproportionately affected by the deregulation of local banking markets.

We also consider which types of inventors are more likely to move out of deregulated states using the same three inventor characteristics: young inventors, forward-looking productive inventors, and backward-looking productive inventors. In Column (3), the coefficient on deregulation interacted with the small employer dummy and the young inventor dummy is positive and significant. Thus, young inventors are more likely to leave small employers for

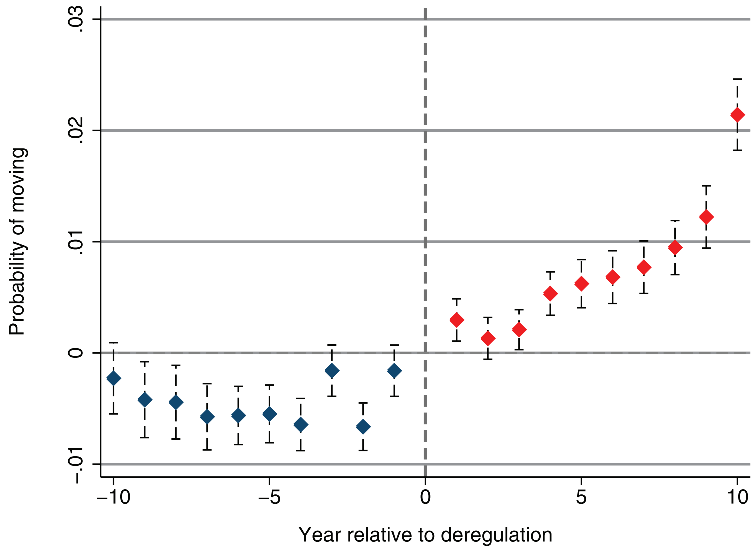

Figure 4
Out-of-state inventor mobility around deregulation events
The figure shows the evolution of out-of-state inventor mobility around deregulation dates. The specification is the same as the first column of Table 7, except that the deregulation index is replaced by a collection of variables $\sum_{s=1}^{3} I^s(k)$, where $I^s(k)$ is a dummy equal to one exactly k years after (or before if k is negative) the state implements a given step of deregulation $s \in \{1,2,3\}$. We plot the point estimates for $k=-10,\ldots,10$, using the deregulation year $k=0$ as the reference year, as well the 95% confidence interval using standard errors clustered at the state level.

out-of-state firms after deregulation. Columns (4) and (5) show a similar effect for more productive inventors, who tend to move out-of-state after deregulation when they initially work for a small innovative firm.[15]

Finally, we analyze whether the pattern of across-state inventor mobility depends on deregulation in the destination state. By a similar argument as for why inventors shift to larger firms when they move within a deregulated state, inventors should shift to larger firms when they move to deregulated states. To test this hypothesis, we regress the ratio of new employer size to previous employer size on the deregulation index of the *destination* state using the same set of controls and fixed effects. The coefficient, reported in Column (1) of Table 8, is positive and statistically significant. Therefore, on average, inventors shift to larger firms when they move to deregulated states. In Columns (2)–(4), we find that this pattern is more pronounced for young inventors and for inventors who have been more productive in the past. Therefore, the flow of inventors out of small firms in deregulated states is not offset by an inflow of inventors.

[15] We show in Online Appendix 0.2 that these patterns of out-of-state moves away from small firms are stronger in relationship-dependent industries.

Table 8
Inventor mobility out of state: Deregulation in the destination state

	New employer size/ previous employer size *(Only inventors moving out-of-state)*			
	(1)	(2)	(3)	(4)
Deregulation destination state	0.13***	0.059	0.14***	0.097**
	(0.00045)	(0.25)	(0.006)	(0.013)
Deregulation destination state × young inventor		0.11***		
		(0.0047)		
Deregulation destination state × forward-looking productive inventor			0.0018	
			(0.97)	
Deregulation destination state × backward-looking productive inventor				0.11**
				(0.025)
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	13,879	13,879	13,879	13,879
Adjusted-R2	0.032	0.036	0.036	0.032

Inventor data were compiled by Lai, D'Amour, and Fleming (2009), from 1975–1998. We estimate linear regression models on the sample of inventor-year observations corresponding to a move to another state. The dependent variable is the ratio of new employer size over previous employer size. All regressions include state, year, and industry fixed effects, the same set of state-year control variables as in Table 2, and inventor age. In Column (1) the explanatory variable of interest is the deregulation index of the new employer's state. In Column (2) we add a young inventor dummy (equal to one if inventor age is below median) and its interaction with the deregulation index, with the state and year fixed effects. In Column (3) we replace the young inventor dummy by the forward-looking productive inventor dummy equal to one if her forward number of patents is above industry-year median; and in Column (4), by the backward-looking productive inventor dummy equal to one if her backward number of patents per year is above industry-year median. Standard errors are clustered at the state level.

Overall, the analyses of within-state and out-of-state mobility offer consistent results. They show that banking deregulation leads to reallocation on the labor market for inventors. This reallocation process appears both across firms, as inventors leave small firms for larger firms that are less affected by deregulation, and across states. This pattern of reallocation is also more pronounced for young and talented researchers.

4. Is the Timing of Deregulation Random?

In this section, we investigate the identification assumption that the timing of deregulation is exogenous to innovation patterns. Kroszner and Strahan (1999) show that the timing of deregulation is not random across states and is related to interest group factors, such as the prevalence of small banks and small firms. This non-randomness can compromise our identification strategy if the timing of deregulation is related to changes in innovation other than through the causal effect of deregulation that we seek to identify. Of course, it is not possible to directly test the identification assumption. Nevertheless, we conduct several tests to alleviate endogeneity concerns.

Reassuring evidence is provided by Figures 2, 3, and 4, which show that changes in innovation activity and inventor mobility do not lead the adoption of state-level deregulation. To develop more formal tests, we investigate how the timing of deregulation is related to potential determinants of innovation. Following Kroszner and Strahan (1999), we model the "duration of regulation" (or the "time until deregulation") using a Weibull proportional hazards model. The hazard rate function takes the form:

$$h(t, X_t, \beta) = h_0(t)\exp[X_t'\beta], \tag{2}$$

where X_t is a vector of time-varying covariates; β is a vector of unknown parameters; and the baseline hazard rate, $h_0(t)$, is pt^{p-1} with shape parameter p. The parameters β and p are estimated by maximum likelihood. We estimate the model separately for the three types of deregulation (formation of multibank holding companies, branching through M&As, and *de novo* branching). Following Kroszner and Strahan (1999), we focus here on the results for branching deregulation through M&As and refer the reader to Online Appendix 0.3 for the results on the two other types of deregulation.

The analysis includes the 39 states that did not deregulate branching through M&As before 1970. We have one observation for each state in each year up to and including the year of deregulation, which yields 608 observations. Table 9 reports the scaled coefficients $\beta^* = -\beta/p$, where p is the Weibull shape parameter. These coefficients have an intuitive interpretation: the log expected time to deregulation is equal to $X_t'\beta^*$; thus, the β^* coefficients represent the percentage change in the time to deregulation for a one-unit change in the covariates.

As a benchmark, we start in Table 9, Column (1), by studying the predictive power of the main variables used by Kroszner and Strahan (1999). Consistent with their results, a larger share of small banks delays deregulation, whereas a larger share of small firms leads to earlier deregulation.

Next, we test whether the timing of deregulation is related to state determinants of innovation or to pre-deregulation innovation trends. In Column (2), we consider the same control variables used in our main analysis: number of college graduates, number of doctorates granted, federal funds for R&D, and invested venture capital. In Column (3), we test whether the timing of deregulation is related to the industry mix of the state. Specifically, we compute the share of state GDP in innovative industries, where we define innovative industries as those in the top tercile of the total number of patents filed in the industry (across the United States) divided by total industry value added.[16] In Column (4), we test whether states deregulate their banking market *following* changes in innovation activity using the growth rate of the number of innovators in the state as the predictive variable. Finally, in Column (5), we test whether the timing of deregulation is related to pre-sample period innovation

[16] The data on state GDP by industry are drawn from the U.S. Bureau of Economic Analysis. We describe how we construct this variable in greater detail in Appendix A.

Table 9
Determinants of banking deregulation

	Duration model for the time until branching deregulation through M&As					
	(1)	(2)	(3)	(4)	(5)	(6)
College graduates		−0.12				−0.02
		(0.22)				(0.18)
PhD graduates		0.12				−0.11
		(0.21)				(0.18)
R&D federal expenses		−0.02				0.04
		(0.05)				(0.04)
VC funds		−0.02				−0.01
		(0.06)				(0.05)
Share of innovative industries			−0.12			−0.15
			(0.37)			(0.95)
Innovation growth				−0.14		−0.13
				(0.18)		(0.11)
Pre-period patent growth					−0.23*	−0.24
					(0.13)	(0.27)
Small bank asset share	4.4***					3.7**
	(1.2)					(1.7)
Capital ratio of small banks	11***					10**
	(3.7)					(4.1)
Relative size of insurance	−0.51					−0.05
	(0.71)					(1.07)
Small firm share	−8.8***					−13***
	(2.4)					(3.9)
Share of Democrats	−0.03					−0.03
	(0.11)					(0.12)
Unit banking indicator	0.27***					0.36***
	(0.09)					(0.13)
Change in bank insurance power indicator	−0.13					−0.17*
	(0.11)					(0.1)
Observations	608	608	608	608	608	608
p-value of χ^{*2}	1.6e–06	0.64	0.75	0.43	0.071	0.00003

We estimate Weibull proportional hazards model in which the dependent variable is the log expected time to intrastate branching deregulation through M&As. There is one observation for each state in each year up to and including the year of deregulation for all 39 states that did not deregulate before 1970. In Column (1) the predictive variables are the following variables from Kroszner and Strahan (1999): small bank asset share is the percent of banking assets in the state held by banks below the median size of banks in each state in each year; capital ratio of small banks is the capital to assets ratio of small banks minus that of large banks; relative size of insurance in the state is measured as gross state product from insurance divided by gross state product from insurance plus banking; small firm share is the percent of all establishments in the state that have fewer than twenty employees; share of Democrats is the share of the three bodies of state government controlled by Democrats; unit banking indicator equals one for states with unit banking restrictions; change in bank insurance power indicator equals one if the state changed the law to permit banks to sell insurance during the sample period. In Column (2) the predictive variables are the same four control variables as in Table 2. In Column (3) the share of innovative industry is the share of state GDP in innovative industries, where we define innovative industries as industries in the top tercile of the total number of patents filed in the industry (all over the United States) divided by total industry value added. In Column (4) innovation growth is the growth rate of the number of innovators in the state. In Column (5) pre-period patent growth is the growth rate of the number of patents filed in the state over the 8-year period preceding the sample period. In Column (6) we use all the previous variables as predictors. Standard errors are clustered at the state level.

growth, which we measure as the growth rate of the number of patents filed in the state over the eight years before the sample period.[17] The idea is that, if the

[17] Specifically, we compute the growth rate of the number of patents granted between 1963 and 1970. In the remainder of this paper, we use the application year, but before to 1969, only the grant year is available in the

innovation process is either persistent or mean reverting, then the pre-period innovation trend may affect innovation patterns during the sample period.

None of these variables have significant predictive power for the timing of deregulation except pre-period innovation growth, which is significant at the 10% level in Column (5), where it is used as the only explanatory variable. The negative sign indicates that states that experienced strong patent growth during the 1960s deregulated their banking market earlier. However, this effect is economically small: a one-standard-deviation increase in pre-period innovation growth (equal to 0.28) results in a $-0.23\times0.28=-6.4\%$ change in the time until deregulation, or an approximately 1 year decrease. In Column (6), we include all our variables, controlling for the main variables used by Kroszner and Strahan (1999). In this case, the effect of the Kroszner-Strahan variables remains large and strongly significant, whereas all the variables related to innovation are small and insignificant. Overall, the timing of deregulation does not appear to be related to innovation activity, except perhaps to pre-sample period innovation growth. This may be a problem if there is mean reversion or persistence in the innovation process. In Online Appendix 0.4, we report several tests showing that our results are robust to controlling for trends and for potential mean reversion or persistence.

5. Discussion

Our results show that the shock to lending relationships produced by banking deregulation induces a reallocation of labor from small innovative firms to larger ones. Another dimension along which inventors may be reallocated is across firms of different age, as young firms, on average, are more opaque and may be more dependent on relationship lending than incumbents (Petersen and Rajan 1995). Indeed, following the same method used in the analysis of mobility between small and large firms, we show in Online Appendix 0.5 that deregulation also leads to the reallocation of inventors from young firms to older ones.

Our results that small and young innovative firms are hurt by banking deregulation seem to contradict previous papers showing that increased competition for lending alleviates credit constraints for the average firm and leads to more entry (Black and Strahan 2002; Cetorelli and Strahan 2006; Kerr and Nanda 2009). The contradiction is only apparent after recognizing that innovative firms make up a small—yet crucial for long-run growth—fraction of firms. Given that most small and young firms do not innovate (Hurst and Pugsley 2011), a shock may well move entry and innovation in opposite directions. Our

data. Given that the average (and median) time from application to grant is two years, the 1963–1970 grant-year period corresponds to the 1961–1968 application-year period, which is the 8-year period preceding the sample period. We use the growth rate in the number of patents rather than in the number of innovators because firm identifiers are missing before 1968.

results imply that while banking competition can improve the financing of investment in tangible projects, it also leads to further tightening of financial constraints for innovative firms, particularly for small and young firms. As such, our findings suggest that banking deregulation shifts comparative advantages away from innovative sectors and toward more tangible sectors.

Chava et al. (2013) propose a different interpretation of the decline in innovation following banking deregulation. They argue that U.S. intrastate deregulation led to a weakening of banking competition, which resulted in a reduction in credit to innovators. This is the opposite of our mechanism, which relies on an increase in banking competition. Previous studies of intrastate branching deregulation (e.g., Jayaratne and Strahan 1998; Black and Strahan 2002; Stiroh and Strahan 2003; Cetorelli and Strahan 2006) show that it increases competition, which is consistent with our interpretation. To further distinguish between these competing hypotheses, we follow the methodology of Black and Strahan (2002) in Online Appendix 0.6. The idea is to allow the effect of deregulation to vary with the level of concentration in local banking markets. If the effect of deregulation operates through an increase in banking competition, then it should be stronger in states whose banking markets are more concentrated before deregulation because if the market is already very competitive, then an increase in competition will have a small effect. Conversely, if the effect of deregulation operates through a decrease in competition, then it should be weaker in states whose banking markets are more concentrated.[18] We find that innovation decreases further following deregulation in states with higher initial banking concentration, whereas the effect is insignificant in states with low initial concentration. This result is consistent with our interpretation that deregulation operates through an increase in banking competition, which hurts lending relationships.

Another channel through which deregulation may affect innovation is via M&As. One possibility is that entrepreneurs innovate in order to sell their startups to large corporations. If post-deregulation financing is easier to access, then entrepreneurs will have fewer incentives to innovate, as they will be able to grow internally. This explanation would also predict that the number of takeovers in innovative industries decreases following deregulation. To test this prediction, we proxy for the number of takeovers by large corporations using the number of acquisitions made by firms in Compustat operating in innovative sectors. The tests and results are reported in Online Appendix 0.7. Depending on the specification, we find that takeovers either increase or do not change significantly after deregulation. These findings are not consistent with the incentive explanation. Instead, the weak increase in takeover activity is consistent with our interpretation that credit becomes more difficult to access

[18] Deregulation also leads to larger banks. If the potential for an increase in bank size is lower when the local banking market is initially more concentrated, then this effect tends to dampen the effect of deregulation when banks are more concentrated.

for innovative startups, whose only possibility to grow may be to be taken over.[19]

Finally, we report and discuss a battery of robustness tests of the number of innovators and inventor mobility analyses in Online Appendix 0.6 using placebo deregulation dates, controlling for interstate banking deregulation, testing the deregulation index non-parametrically and excluding the most innovative industries or states.

6. Conclusion

We provide insight into the drivers of innovation and the capacity of an economy to finance its innovative sectors. Employing patent- and inventor-level data, we show that banking deregulation has an adverse effect on small innovative firms, which in turn leads to the labor market reallocation of inventors across firms and states. Our results suggest that the ability of banks to address soft information is critical to alleviating information friction, especially for opaque borrowers such as innovative start-ups. While the increase in competition for lending reduces financial constraints for the average firm (Jayaratne and Strahan 1998; Black and Strahan 2002; Cetorelli and Strahan 2006; Kerr and Nanda 2009), which invests in more tangible projects, our results show that it leads to further tightening of financial constraints for innovative firms, particularly for small ones. Taken together, these findings indicate that banking deregulation may shift comparative advantages away from innovative sectors to more tangible sectors. This shift in specialization may not necessarily slow down growth, especially over the short run. However, given that innovation generates spillovers, reshaping comparative advantages might impede long-run growth. Moreover, as argued by Acemoglu et al. (2013), the reshaping of comparative advantages within innovative sectors and across firms of different size can further affect the long-term pace and direction of technological change.

Our results can shed some light on the drivers of comparative advantage around the world. One European puzzle is why France lags behind Germany in high-technology sectors. The structure of their respective banking markets offers a potential explanation. Whereas France is dominated by a small number of large national banks, Germany is characterized by multiple regional banks that have close relationships with their debtors. In terms of public policies, if one accepts that the lesson drawn from commercial banking extends to public funding, then governments willing to support innovation by allocating public funds should not rely on a centralized and hierarchical structure but on local agencies that are better able to address soft information.

[19] M&A activity might also increase if takeover demand increases. If this is the case, Phillips and Zhdanov (2013) show that it would increase potential targets' incentives to innovate, which would lead us to underestimate the negative effect of deregulation on innovation.

Finally, we provide evidence that banking markets play a role in the reallocation of skilled human capital across the economy, which may have implications for local productivity, knowledge spillovers, and urban agglomeration (Moretti 2012). Given that governments have become increasingly aware of the importance of winning the "global race for inventors' brains" (Fink, Miguélez, and Raffo 2013), understanding the determinants of skilled human capital migration has important policy implications.

Appendix. Construction of Industry-Level Variables

A.1 Relationship Dependence

We use the National Survey of Small Business Finances (NSSBF), which is available on the Fed website. The first proxy of relationship dependence is the average distance from the main lender in the 1987 survey (variable r6481) by two-digit SIC industry. The second proxy is the growth rate of the average distance from the main lender between 1987 (variable r6481 in the 1987 survey) and 1998 (variable idist1 in the 1998 survey). The third proxy is the average length of relationship with the main lender. Note that length of relationship is mechanically correlated with firm age because only an old firm can already have a long-standing relationship with its bank. To filter out, we regress log of length of relationship (variable r3311 in the 1987 survey) on log of firm age (1987 minus the 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 cannot use these variables directly in our regressions because patent data use a different industry classification. To map SIC codes into patent technology classes, we merge the NBER Patents File with Compustat (the patent data include the GVKEY of public innovators) and compute, for each patent technology class i, the fraction $w_{i,j}$ of innovators in this technology class that belongs to SIC j. We then compute for each technology class the weighted average of the relationship-dependence proxies across all SIC codes where the weights are the $w_{i,j}$'s.

A.2 External Financial Dependence and Asset Tangibility

We start from Compustat and keep all non-financial firms during the sample period 1968–1998. We compute firm-level external financial 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 three-digit SIC level. Asset tangibility is defined as property, plant, and equipment (item #7) divided by total assets (item #6). We then use the same procedure as for the relationship-dependence variables to map these variables into the patent technology classes that we use in our regressions.

A.3 Innovative Industries

To define innovative industries, 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 5 years. We then use a 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. Therefore, our measure of industry-innovation intensity is time-varying to account for the fact that the distribution of patents across industries has changed over time.

A.4 Innovator Size

Firm size is calculated as the number of patents filed by the firm in a given year. Firms are classified as large or small based on whether their size is below or above the median firm size in the same industry-year.

A.5 Young Inventors and Backward- and Forward-Looking Productive Inventors

The young inventor dummy is equal to one if inventor age, defined as the time elapsed since the inventor first filed a patent, is below the industry-year median. The backward-looking productive inventor dummy is equal to one if the inventor's number of past patents divided by the inventor's age is below the industry-year median. The forward-looking productive inventor dummy is equal to one if the inventor's number of future patents is above the industry-year median.

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