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Banking integration and growth: Role of banks' previous industry exposure

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ABSTRACT

Using U.S. interstate banking deregulations, we identify the effect of market-entering banks' prior industry exposures on the manufacturing sector growth in the new state that they enter. We create banking integration and industry specialization measures that consider both direct (state-pair) as well as indirect (tertiary-state) links created by expanding multi-bank holding company networks. First, consistent with the economic mechanism we have in mind, we observe that banks' home state's industrial specialization is positively correlated with their lending specialization when participating to in-state as well as out-of-state syndicated loan markets. Then, focusing on industry value added at the state-industry-level, we find evidence consistent with the positive impact of market-entering banks' prior exposure to a sector on the growth of that industry in the newly-entered state. The observed effect is larger when the state-pair-level discrepancy in sector-specialization is greater. Our findings are robust and hold in capital-related components of industry-level value added. We observe that the above results are more prominent in sectors that are more external finance dependent, have lower amounts of physical capital that can be pledged as collateral, generate more valuable patents, are durables-producers, and have a higher risk. Our findings suggest that a bank integration channel helps shape states' industrial landscape.

1. Introduction

Over the past four decades states (countries) became more integrated financially, in many instances through out-of-state (foreign) bank entry. For example, banking deregulations in the U.S. have led to the emergence of financial conglomerates that operate with few geographic restrictions within the 50 states of the Union.[1] A similar trend is also developing in the E.U. where member countries' economies are increasingly connected through the banking sector. Such financial integration is shown to lead to the synchronization of states' output fluctuations (Morgan et al., 2004; Goetz and Gozzi, 2020), reallocation of capital (see Fisman and Love, 2004, for international evidence; Acharya et al., 2011, for the U.S.; and Bekaert et al., 2013, for the E.U.), reallocation of labor (Bai et al., 2018), and changes in total factor productivity (Krishnan et al., 2015).[2]

We contribute to this area of research by focusing on a dimension of credit provision that has been overlooked in this literature: market-entering financial institutions' pre-entry familiarity with particular industries. We treat outside-finance as a factor of production,[3] and explore the sector-level growth impact of banks' previous industry-specific

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[1] While Interstate Banking and Branching Efficiency Act (IBBEA) of 1994, also known as the Riegle-Neal Act, allowed coast-to-coast banking in the U.S., it also initially allowed the states to opt out some of its provisions by putting limits on branch-based entry (e.g., Rice and Strahan, 2010).

[2] Evidence also indicates that interregional banking integration leads inter alia to more firm entry (e.g., Cetorelli and Strahan, 2006), higher industry turnover (Kerr and Nanda, 2009), more interregional trade (Michalski and Ors, 2012), and higher industry growth (e.g., Bruno and Hauswald, 2014).

[3] For example, Rodano, Serrano-Velarde, and Tarantino (2018) find that when Italian banks abruptly tighten their lending standards, investment, production and employment fall for the marginal firms that had enjoyed credit access during the periods of lax credit standards.

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expertise when they enter new markets. If such sector-specific expertise has value when making loans, we should observe a higher growth in less developed sectors located in markets into which banks with a know-how specific to that particular industry enter. Put differently, the integration of a state's banking system with out-of-state lenders should lead to higher growth of its less prominent industries if some of the entering institutions have specific expertise in lending to those sectors. By testing this hypothesis, we not only contribute to the research on the real economy impact of sector-specific knowledge of financial institutions (e.g., Bernstein et al., 2017), but also to the larger area on banking and growth (e.g., Levine, 1997 and 2005) by examining one of its channels.

The underlying mechanism we have in mind is that of better loan screening in an under-developed industry by market-entering banks that have accumulated superior expertise in information collection and processing in that particular sector prior to their entry.[4] During the period that we study, inter-state bank-entry occurred through Multi-Bank Holding Companies' (MBHCs') expansions beyond their "home" states through acquisitions of depository institutions in "host" states. We posit that, beyond a simple provision of additional credit across all sectors, the industry-specific lending expertise of entering banks would give them a comparative advantage via their ability to better screen and monitor loans in that same sector in the new markets that they enter. This could happen through the specialization of lending officers in other lending markets or the development of proprietary credit scoring systems using the associated loan data. The MBHC would serve as a network for the sharing of such expertise as loan officers are appointed or when credit scoring systems are shared with the newly acquired banks.[5] As such, a multi-state MBHC acts as a conduit for sharing expertise developed in different industries in different states (and not limited to the state in which the institution has its largest presence, which is typically where it is headquartered).

To test our hypothesis, we rely on the U.S. data that have a number of advantages. First, banking integration is shown to affect the real economy in the U.S. (e.g., Morgan et al., 2004, Cetorelli and Strahan, 2006, Kerr and Nanda, 2009, Rice and Strahan, 2010, Michalski and Ors, 2012, Goetz and Gozzi, 2020). Given this evidence, our focus here is to test whether banks' industry-specific knowledge matters for the related sectors in the local economy of the new state that they enter. Second, during the years that we study, the banking sector formed roughly one-fifth to one-third of the U.S. financial sector. So, any effect that we observe in our empirical work is unlikely to be economically marginal given the prominence of banks in the intermediation process during the period we examine. Third, we concentrate our study on manufacturing industries that typically face U.S.-wide competition, can organize their activities easily anywhere in the Union, are not subjected state-level barriers to entry, have (in principle) access to the same technology and inputs with similar quality, and whose output data are fairly homogenous across different sub-sectors that compose them.[6] Moreover, U.S. manufacturing firms operate in a single and fairly homogeneous economic and legal environment. As such, we do not have to worry about confounding effects (such as, among others, differences in legal systems as documented in La Porta, et al., 1997 and 1998) that cross-country studies have to deal with. Finally, and very importantly, the use of the U.S. data allows us to control for the potential endogeneity of lending institutions' entry: we can instrument banking integration, as in Goetz et al. (2016), thanks to the staggered interstate bank-entry deregulations that took place in different years for different state-pairs.

Our empirical strategy is as follows. First, we define the *specialization* of a manufacturing industry in a state as the ratio of that sector's share of manufacturing output (i.e., value added) to its share of overall U.S. manufacturing output.[7] Second, using a publicly available data source in which we can trace American banks' lending in different domestic industries (albeit with limited coverage, see next paragraph), we test whether there is any empirical support for the economic mechanism that is at the heart of our main hypothesis: i.e., whether industrial specialization in banks' "home" markets gives them a competitive advantage in their "away" markets (where "home" and "away" markets refer to U.S. states). Third, in our main analysis, we use comprehensive state-pair-industry-level data to examine whether there is a difference in the growth rate of industry-level value-added between state pairs following less specialized state's banking deregulation and its financial integration with the more specialized state through entry by the banks of the latter.

We can summarize our findings as follows. First, using DealScan's syndicated lending data, we establish that there is a positive correlation between the industrial specialization of the state in which U.S. banks are headquartered and these institutions' industry-level *lending specialization* in their "home" as well as their "away" lending markets.[8] This evidence, albeit limited to U.S. banks' syndicated lending due to data availability, provides empirical support for the economic mechanism we have in mind for our main hypothesis: (i) banks' headquarter-market industrial specialization makes an imprint on their "home" market lending, and (ii) when lending in "away" markets, banks tend to make loans in a way that reflects their "home" state's industrial specialization. Second, across industries and at the state-pair level, we observe no difference between the growth of sectors located in states that are less versus more specialized in them. This observation is important, because it allows us to rule out the possibility that our results can be due to a general tendency for mean reversion in sector-level growth measures. Then, we conduct sets of regressions, using different test variables and estimators, in which we control for a large set of confounding factors by including state-year effects, industry-year effects, state-pair-industry effects, and implicitly controlling for any common shocks at the state-year level for the compared industries (since our dependent variable is differential growth of a sector between a pair of states).[9] Consistent with our hypothesis, we observe a higher growth *differential* for the value added of manufacturing industries in which a given state is less

[4] There is a large literature on the special role that banks play in screening firms and easing credit constraints: e.g., Aghion, Howitt, and Levine (2018) for a review with a theoretical perspective.

[5] For the growth dynamics due to financial innovation, see Laeven, Levine, and Michalopoulos (2015).

[6] This is not necessarily true for agriculture, mining or some service industries (e.g., electricity generation or shipping) where the natural endowment is decisive for the location choices. It is also not true for service industries (e.g., real estate, retail) where the local demand is important or various laws might limit industry growth (financial services in the U.S. prior to 1980s being an example). Moreover, the capital intensity of the services sector is typically lower than that of manufacturing. Such considerations prevent conducting proper testing for the effects that we study in this paper for industries other than manufacturing.

[7] Put differently, for each manufacturing industry, we calculate the ratio of that sector's contribution to the Gross State Product (GSP) to its contribution to the U.S. Gross Domestic Product (GDP). This *specialization* index adapts that of revealed-comparative advantage proposed by Balassa (1965) to the context of U.S. state industrial production, a standard approach in regional economics and international trade studies. An under-specialized (over-specialized) industry would have a ratio less (higher) than one.

[8] DealScan is the only *publicly available* data source in which we can trace US banks' lending to different sectors in the syndicated loan market. The more comprehensive and detailed Shared National Credit Program dataset, which is maintained by the US banking regulators, is confidential and inaccessible to researchers outside the FDIC, the Fed, and the OCC (e.g., Mian and Santos, 2018).

[9] As described further below, our state-pair-industry-level dependent variable is constructed such that the growth of a given industry in the less specialized state is always benchmarked on the growth of the same industry in the more specialized state of the pair. This approach allows us to refine our tests: if our conjecture holds true, we should observe an effect that increases with higher difference in sector-specialization between a state-pair (as of the date of deregulation).

specialized in, when that state's banking system gets integrated with that of another state that is more specialized in the same sectors. Our preferred IV-model's coefficient estimates exhibit reasonable but economically relevant magnitudes: we find that for under-developed industries, a one standard deviation increase in banking integration of their state (which is equal to 0.0620 in our sample) with the states whose banks are more specialized in the same industry, leads to roughly a 1% higher growth per year in value added. These results are robust to differences in estimation methods, calculation of growth, estimation period, and the fixed effects included in the regression. In fact, we obtain sharper results when we interact integration with a high and low (with respect to the median) differences in initial state-pair industry specializations: the differential growth of value added after banking integration (in IV-regressions) is larger when the initial specialization dissimilarity is higher. Our findings on overall industrial convergence are consistent with the evidence in Kim (1995), Dumais et al. (2002), and Acharya et al. (2011). They are also consistent with evidence on output-synchronization across states (Morgan et al., 2004) and at the state-industry level (Goetz and Gozzi, 2020).

Then, we investigate the possible economic channels that could be driving our results. We find that the estimated effects are larger for sectors that (i) are more dependent on external finance (as in Goetz and Gozzi, 2020), (ii) have lower physical assets (as a fraction of total assets) that can serve as collateral for loans, (iii) generate more valuable patents (or alternatively, relatively more patents), (iv) are more risky (as measured by Scholes-William betas of listed companies in that sector), and (v) are producing durable-goods. Our findings also suggest that greater information flows following banking integration may lead to different specialization outcomes than those resulting from risk sharing generally obtained through cross-regional asset holdings (e.g., financial assets or FDI claims) by agents in the economy (e.g., Kalemli-Ozcan, Sørensen, and Yosha, 2003).

In what follows, Section II reviews the relevant literature; Section III details the empirical approach and the data; Section IV presents the results; and Section V concludes.

2. Related literature

Our paper is connected with different areas of the literature on financial integration and economic growth. There is a well-established research area on the growth of industries given the financial development of countries.[10] A strand of this literature focuses on the U.S., and relies, as we do, on interstate banking deregulations for the purposes of identification. For example, Cetorelli and Strahan (2006) find that, following U.S. interstate banking deregulations, the resulting higher banking competition is associated with the growth of small firms at the expense of large ones; whereas Kerr and Nanda (2009) document that small firm entry and exit (the so-called "churning" effect) increases. Krishnan et al. (2015) find that TFP of small firms' increases following higher branching deregulation in the U.S., while Bai et al. (2018) results suggest that banking deregulation is associated with significant convergence in the labor marginal revenue product gap of young firms with different productivity. In contrast to the above papers, we show that an industry's post-deregulation growth is affected by entrant-banks' prior exposure to that sector. In fact, our paper contributes to the larger literature on finance and growth (e.g., Levine, 1997, 2005), by providing evidence that sector-level expertise of banks affects industrial growth differentially: state-level (or country-level) industrial growth, and hence industrial composition, appears to be influenced by market-entrant financial institutions' prior industry-knowledge.

Our paper is also closely related with a literature that examines the effects of financial integration across states or countries. Morgan et al. (2004) using state-level data, and Goetz and Gozzi (2020) using state-industry-level data, find that banking integration across states helps smooth regional output fluctuations in the U.S. while the risk of transmission of macroeconomic shocks across states increases. Acharya et al. (2011) observe that following the removal of interstate bank branching restrictions not only did the states' output volatility decreased, but that states' industrial portfolios started to converge towards a common U.S. benchmark, with the effect being driven by sectors with a larger share of young, small and external finance dependent companies.[11] Michalski and Ors (2012) show that the state-pairs that experience higher banking integration trade more compared to non-integrated states. The above-cited results on the reallocation of capital across sectors and regions (states or countries), suggest that banks' lending policies can affect the industrial growth.

The paper that comes closest to ours is Bernstein et al. (2017), who find that following private equity (PE) firms' investment in a country, the industries in which these financial institutions specialize enjoy higher total production, value added, total wages and employment growth. While our results complement Bernstein et al. (2017), our paper differs from theirs. First, we use the U.S. interstate banking deregulations as a series of quasi-natural experiments to identify the industry growth effects of (potentially endogenous) financial integration through the banking sector. In contrast, pinning down identification is much harder in a cross-country setting, as other concurrent developments in countries' financial sectors can influence sector-level growth.[12] Importantly, in the U.S. setting that we rely on, other segments of the financial sector (for example, investment banking) did not exhibit similar patterns of *entry* and *integration* for the same state-pairs during the same years. Second, in the period that we study, commercial banks owned roughly 1/5th to 1/3rd of the total assets of the U.S. financial sector (Financial Accounts of the United States, 2014), making any impact that they had economically relevant. Finally, existing research provides evidence of state-industry-level output synchronization across U.S. states following banking integration (Goetz and Gozzi, 2020). We examine the one of the economic channels that underline such convergence.

[10] E.g., Rajan and Zingales (1998); Wurgler (2000); Levine, Loayza, and Beck (2000); Fisman and Love (2004); Bertrand, Schoar, and Thesmar (2007); Levchenko, Rancière, and Thoenig (2009); Friedrich, Schnabel and Zettelmeyer (2013); Bruno and Hauswald (2014); Larrain and Stumpner (2017); and Gopinath et al. (2017).

[11] Similar convergence is documented to occur with deeper financial development among OECD countries by Manganelli and Popov (2015). In a similar vein, Bekaert et al. (2013) observe reductions in European intra-sector growth differentials following this economic region's financial (albeit through equity market) integration. Somewhat at odds with these papers, Kalemli-Ozcan, Papaioannou, and Peydro (2013), using international data, find that increases in cross-border broad asset and liability bank holdings lead to a divergence of economic activity between impacted regions. However, such a broad measure of asset links between banks may not reflect information transmission in shaping lending, underlined in this paper.

[12] For example, Behn et al. (2014) use international data and find evidence of industry-level growth after major financial deregulations.

Our hypothesis requires that industry-specific information be shared among banks belonging to a MBHC, as these holding companies expand into new states.[13] Sector-specific expertise flows between banks of the financial conglomerate are to be expected given the evidence indicating that information sharing does occur across bank and *non-bank subsidiaries* of the same MBHC. For example, Gande et al. (1997) show that during securities issuance, MBHCs fulfill a certification role in a way that is consistent with a flow of information from the commercial banks to investment banking (the so-called Section 20) subsidiaries of the same financial conglomerate. Similarly, examining the portfolio choices of mutual funds that are proprietary to MBHCs, Massa and Rehman (2008) find that the former significantly increase their investments in firms borrowing larger amounts from MBHC-affiliated banks, consistent with information flows from the banking subsidiary to the mutual fund subsidiary.[14]

Finally, there is another strand of the literature (Winton, 2000, and Stomper, 2006) that makes theoretical arguments for the sector-level specialization of banks in their lending.[15] There could be a learning-by-doing mechanism at work where banks obtain returns to scale by specializing. However, the related empirical evidence to date is mixed.[16] That said, for our conjecture to go through we do not need banks coming from states that are more specialized in certain industries to be themselves institutions specialized (or focused) in lending primarily to these sectors. The fact that these banks would have more information regarding these sectors (in which their state is more specialized) *relative* to banks in their newly-entered markets would suffice. If this point is true, the effects that we have in mind ought to be stronger for state-pairs that have large differences in their specializations in a given industry (keeping in mind that state-level specializations of sectors serve as a proxy for the expertise of banks therein).

In the next section, (a) we explain the potential problem of endogeneity that we face and how we solve it, (b) how we measure banking integration and (c) industry-specialization in considering the network structure of MBHCs, together with (d) our empirical set-up, and (e) the data with which we estimate them.

3. Identification, empirical specifications, and the data

3.1. Identification

We hypothesize that less developed industries would grow faster if the state in which they are located experiences banking integration with other regions via institutions that have a comparative advantage in lending to those sectors. In our setting, banks' comparative advantage in one sector arises because of the larger prominence of that industry in the other states in which these institutions already operate. Ideally, a direct test of this hypothesis would involve industry composition of bank loan portfolios before and during the integration process.[17] Unfortunately, such industry-level decomposition of bank lending is not available for the U.S.[18] As a consequence, we rely on state-industry-year level data and regress the annual state-pair-level differences in growth rates of industries on a test variable that captures state-pair's banking integration. We do this by focusing on the growth of under-developed industries in the host state (see sections 3.2 and 3.4 below). However, such regressions would be biased and inconsistent if bank-integration is endogenous to industry structure in general, and industry growth potential in particular.

From one point of view, endogeneity is not likely to be a major concern, as the existing evidence on the political economy of interstate banking deregulation does not attribute a role to lobbying by non-financial industries (Kane, 1996 or Kroszner and Strahan, 1999). Even if non-financial industries were to play a role in interstate banking deregulations, it is highly improbable that the industries in which a state is less specialized (i.e., smaller sectors in that state), and on which we focus, would be the driving lobbying force for interstate bank-entry deregulation at the state legislatures. Nevertheless, even if the deregulation process is unlikely to be endogenous to the growth of less specialized industry segments, some banks' entry decisions might be endogenous: if some MBHCs' entry may have been driven by opportunities in lending growth, our banking integration might be endogenous to industry's growth potential.

To deal with this potential problem of endogeneity, we rely on the quasi-natural experiment set-up provided by the staggered state-pair-level interstate banking deregulations that took place in the U.S. during 1980s and 1990s. We follow Goetz et al. (2016), to create a time-varying instrument of *predicted* MBHC-level inter-state entry, using the local (MSA) market-level deposit data to estimate the following gravity-type regression (which follows from the "Stage Zero" regression in Goetz et al., 2016):

[13] For the role and importance of credit scoring systems in bank lending in the U.S. refer to Frame, Srinivasan, and Woosley (2001), Akhavein, Frame, and White (2005), and Berger, Frame, and Miller (2005), among others.

[14] Additional evidence exists in non-bank financial institutions. Luo, Manconi and Schumacher (2015) find that target (acquirer) mutual funds start investing in sectors that the acquiring (targeted) mutual fund used to invest in prior to the acquisition. More pertinent for our conjecture, Schumacher (2018) finds that when investing abroad, international mutual funds overweight the largest industry segments of their home countries (i.e., the sectors they are more exposed to in their home country).

[15] Winton (2000), studying the costs and benefits of lending diversification, provides theoretical arguments suggesting Modern Portfolio Theory-based lending may not be the optimal strategy if monitoring is costly and loans have important downside risk (i.e., it may pay off to specialize under certain conditions). Stomper (2006) suggests that industry-expert banks may extract rents that are proportional to the sector-specific risks that they take: This would lead to a banking market equilibrium in which certain banks specialize in lending to certain sectors, leading to a sector-level concentration in lending.

[16] Using Italian data Acharya, Hasan, and Saunders (2006) find that diversification of banks' industrial lending does not guarantee higher portfolio performance, suggesting that there may be benefits to specialization. Hayden, Porath, van Westernhagen (2007) find that lending to certain sectors generally increases loan portfolio performance, but not necessarily in the way anticipated by Winton (2000) or found by Acharya, Hasan, and Saunders (2006). More recently, Tabak, Fazio and Cajuerio (2011) use Italian data and find that industry-specialization leads to higher portfolio returns and lower risk. In a similar vein, Böve, Düllmann, and Pfingsten (2010) observe that specialization leads to better monitoring by German banks, whereas Jahn, Memmel, and Pfingsten (2013) find that these institutions' specialization reduces loan write-offs. Degryse, Kokas, and Minetti (2021), using syndicated loan data, provide evidence that banks sectoral lending experience compensates for their lower monitoring effort. In contrast, Beck and De Jonghe (2013) examine an international sample of large banks and find that sector-level specialization generates higher volatility and lower returns Paravisini et al., 2020.

[17] We know of no evidence on post bank-acquisition portfolio convergence for commercial loans at the sector level, even if there is limited anecdotal (e.g., Murray, June 3, 1996) and empirical (e.g., Zarutskie, 2013) evidence on banks portfolio harmonization across loan categories (i.e., business, real-estate, and personal loans, etc.).

[18] The detailed quarterly financial statements (the so-called Call Reports) that all the U.S. commercial banks have to file with their federal regulators do not contain a break-down of loans by underlying industrial sectors.

$$SHARE_{b,m,n,t} = \beta_0 + \beta_1 HQSTATE_{b,n,t} + \beta_2 Ln(DISTANCE_{m,n}) + \beta_3 HQSTATE_{b,n,t} \times Ln(DISTANCE_{m,n}) + \beta_4 Ln\left(\frac{POPULATION_{m,t}}{POPULATION_{n,t}}\right) + \beta_5 HQSTATE_{b,n,t} \times Ln\left(\frac{POPULATION_{m,t}}{POPULATION_{n,t}}\right) + \varepsilon_{b,m,n,t} \quad (1)$$

where, $SHARE_{b,m,n,t}$ is the percentage of deposits of MBHC b, headquartered in the metropolitan statistical area (MSA) m and held in the branches of its affiliated banks in MSA n in year t. $HQSTATE_{b,n,t}$ is an indicator variable that is equal to 1 if MSA n is in the same state as the MBHC's headquarter MSA m, and 0 otherwise: we follow the regional trade literature on home-country bias (Wolf, 2000, and Hummels and Hillberry, 2003), and explicitly account for the fact that it is easier for a MBHC to expand into another MSA of the same state in which it is headquartered than it is to enter an MSA located in another state. Ln$(DISTANCE_{b,n})$ is the natural logarithm of the miles between MBHC b's headquarter located in MSA m and the center of MSA n, and captures the so-called "gravity effect" between markets. Ln$(POPULATION_{m,t}/POPULATION_{n,t})$ is the natural logarithm of the ratio of the population of MBHC b's headquarter MSA m to the population of MSA n in year t, and accounts for the attractiveness of the deposit market n with respect to deposit market m.

Using Federal Deposit Insurance Corporation (FDIC)'s Summary of Deposits data covering the years 1984–1997, we estimate regression Eq. (1) with both OLS and fractional logit estimators, and present the results in Appendix Table A2. As in Goetz et al. (2016), during the estimation we only include observations in which it is legally feasible for a MBHC b with headquarters in MSA m to enter MSA n during year t; the predicted *SHARE* values are set to zero for MSA pairs for which entry was not legally possible. The predicted MBHC-level $\widehat{SHARE}_{b,m,n,t}$ estimates (also for 1982 and 1983, where applicable) are then aggregated at the state-pair *i-j* level and serve as the only instrumental variable in our IV-regression models. Given that the series of constructed-IVs obtained from the OLS and fractional logit estimators have a correlation above 0.8, we go along with the simpler model's predictions: we use the predicted values (censored at zero) of $\widehat{SHARE}_{b,m,n,t}$ from a pooled-OLS regression.

3.2. Measuring industry specialization

In all of our main regressions, the dependent variable is $\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$, i.e., the differential growth of value added (*VA*) of sector *s* in state *i* and year *t* ***relative*** to the growth of the same sector *s* in state *j* and year *t*, with *i* (*j*) being the less (more) specialized state of the pair in sector *s* as of the date of effective interstate deregulation for state pair *i-j*.[19]

This approach requires that we clarify the way we measure industrial specialization of a state: as specialization differences between the state-pair *i-j* are also likely to be influenced by the specialization exposures that banks located in states *i* and *j* might be exposed to through their presence in other states *k, l*, etc., each with its own industrial specialization characteristics. To deal with these issues, we proceed as follows:

First, we calculate the annual state-level industrial specialization ($Industrial\_Specialization_{i,s,t}$) for each of the 19 two-digit SIC manufacturing industries as the ratio of a sector *s*'s share in state *i*'s output (i.e., value added) to the same sector's share of overall U.S. output.[20] We also come up with a sector-level bank lending-specialization measure. This lending specialization index allows to test for the economic mechanism that is a pre-requisite for our main hypothesis: banks' entry into new markets can influence growth of the sectors in which these institutions have a competitive advantage in making loans only if the sector composition of banks' "out-of-state" lending is correlated with their "home"-state's industrial specialization. For this, we use the DealScan dataset, and calculate $Lending\_Specialization_{i,s,t}$ as the annual ratio of a sector *s*'s share in the syndicated lending (to non-financial corporations) of U.S. banks headquartered in state *i* to the same sector's share of overall credit by all U.S. banks participating in syndicated loan market.

Second, in our main analysis, since we use state *i*'s specialization in a sector *s* as a proxy for *i*'s banks' expertise in *s*, we account for the industry specialization differences at the state level that might be due to state *i*'s MBHCs presence in *other* states *k, l*, etc., as follows. For each multi-state MBHC, we calculate that institution's fraction of banking assets held in each state in which it has a presence. These fractions add up to 1.0 for each multi-state MBHC. Then, for each MBHC, we multiply the fractions of assets held in different states, with the industry-level specialization indexes of each of these states. This generates a MBHC-and-sector (i.e., *b-s*) level weighted-average industry specialization, which we attribute to the holding company's headquarter state *i*. Next, for each state *i*, we calculate the share of total assets of each MHBC. These total asset shares add up to 1.0 at the state level. In a final step, we multiply the MBHC-sector level weighted-average specialization variable with the state-level share of that MBHC's banking assets in the state in which it is head-quartered. This procedure generates a state-sector-year-level specialization index $SPECIALIZATION_{i,s,t}$. This variable considers the industry-*s* exposure of any state *i* via the asset holdings of the MBHCs headquartered in it in other states *k, l*, etc.

3.3. Measuring banking integration

Like specialization, our measure for the banking integration between state-pairs takes into account these states' direct as well as indirect banking connections. Direct banking integration between state-pair *i-j* occurs through banks that MBHCs headquartered in *i* and *j* own in *j* and *i*, respectively. Direct integration is defined as the sum of common banking assets belonging to MBHCs headquartered in either of the two states *i* and *j* in a given year *t* divided by the total of all banking assets in both states in the same year. *Indirect* banking integration takes into account the presence that the MBHCs headquartered in state *j* might have, for the sake of example, in states *k* and *l*. In such cases we also calculate banking integration between state-pairs *i-k* and *i-l*, calculated the same way as the one between *i-j*. Then we obtain our banking integration variable for state-pair *i-j* as of year *t* ($INTEGRATION_{i,j,t}$) by adding up

[19] $\Delta ln(Y_{i,s,t})$ is the growth of sector *s* in state *i* and year *t*, i.e., $\Delta ln(Y_{i,s,t}) = \ln(Y_{i,s,t}) - \ln(Y_{i,s,t-1})$. The order of growth terms is fixed as of the date of effective deregulation of the state-pair and does not change over time, irrespective of changes in specialization of states *i* and *j* in sector *s* over the years that follow.

[20] The number of manufacturing industries (19) with which we can work is imposed on us by the publicly available version of the Census data as provided by the Bureau of Economic Analysis (BEA) – see also Section III.E.

direct integration between *i-j* and indirect banking integration (in the above example, between *i-k* and *i-l* that arise due to MBHCs headquartered in state *j* that also have presence in states *k* and *l*).[21] Henceforth, for the sake of simplicity we refer to integration between state-pairs (*i-j*) in our discussion, even though $INTEGRATION_{i,j,t}$ includes both direct and indirect integration, as explained above.

3.4. Empirical specifications

In a first step, we examine whether there is any support for the economic mechanism that is a pre-requisite for our hypothesis: namely, whether banks' industry-level lending patterns are influenced by their home-state's industrial specialization characteristics. To do so we estimate the following regression equation with in-state and out-of-state lending samples as a pooled-OLS regression (or as a cross-sectional OLS after aggregating the data):

$$Lending\_Specialization_{i,s,t} = \beta \times Industrial\_Specialization_{i,s,t} + \delta_i + \delta_s + \delta_t + e_{i,s,t} \tag{2}$$

where, *Lending_Specialization* and *Industrial_Specialization* are as described above; and δ_i, δ_s, and δ_t are the fixed-effects for state *i*, sector *s*, and year *t*, respectively.

In our main analysis, we use the following regression equation to examine changes in relative sector-level growth at the state-pair level after interstate banking deregulation:

$$\Delta\ln(VA_{i,s,t}) - \Delta\ln(VA_{j,s,t}) = \beta_1\ L1.DEREGULATED_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t} \tag{3}$$

where, $\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$ is defined as above (under Section 3.2); $DEREGULATED_{i,j,t}$ is an in indicator variable that is equal to one starting with the year *after* (and including all the subsequent years) the state-pair *i-j* effectively opens their markets to each other's banks, and zero otherwise; $\delta_{i,j,s}$ is the state-pair-industry fixed-effect, $\delta_{i,t}$ is the state-year fixed-effect for state *i*, $\delta_{j,t}$ is the state-year fixed-effect for state *j*, $\delta_{s,t}$ is the sector-year fixed-effect, and δ_t is a year fixed-effect; $e_{i,j,s,t}$ is the error term. We estimate Eq. (3) with *Within* regressions.

It should be noted that this specification controls for a number of potentially confounding factors. The differencing of state-level industry annual growth rates implicitly takes out the effects of any common shock that affects a particular industry at the state-pair level in a given year. The $\delta_{i,j,s}$ fixed-effects soak up any unobservables that are state-pair-industry specific and that remain constant over time. As such, any sector-specific differences in initial endowments, or geography related advantages for the state-pair (such as proximity) are accounted for. As a result, the initial tendency of small sectors (that would be among the less specialized ones in a state) to grow faster and large ones to grow slower, something that could otherwise drive our results, would be absorbed by $\delta_{i,j,s}$. Put differently, $\delta_{i,j,s}$ fixed-effects account for any observable or unobservable *pre-conditions*. State-year fixed-effects ($\delta_{i,t}$ and $\delta_{j,t}$) account for state-level changes in economic factors (for example, economic growth at the state level or the effects of state-wide legislation about minimum wages or taxes, etc.). Industry-year fixed-effects ($\delta_{s,t}$) account for time-varying developments in sector *s* at the U.S.-level that could exacerbate the growth of more or less specialized industries. We also have year fixed-effects, δ_t, to account for the growth of the U.S. economy.

In Eq. (3) the dependent variable ($\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$) is at the state-pair-sector-time (*i-j-s-t*) level whereas the test variable ($DEREGULATED_{i,j,t}$) varies at the state-pair-time (*i-j-t*) level.[22] This is likely to render identification weaker, as the test variable ($DEREGULATED_{i,j,t}$) does not carry any ***sector*** specific information. One way to improve on this is to take into account the discrepancy in the industry-level specialization exposure of banks that are involved in the integration of states *i-j* following entry deregulation. The larger is the difference in the specialization exposure to sector *s* of local banks versus that of entering banks following the entry-deregulation for a state-pair, the higher should be the effect that we hypothesize. The largest differences would typically correspond to cases in which state *i* is under-specialized in sector *s* (in which case, specialization would be below one) and state *j* is over-specialized in *s* (in which case, specialization would be above one). Small differences in sector-specific specialization would be similar to comparing growth of industry *s* across a deregulating state-pair *i-j* when both states are similarly under-, over- or not particularly-specialized, thus conveying no informational advantages to banks of state *j* entering state *i*.

To operationalize this improvement in identification, we define $\Delta SPECIALIZATION_{i,j,s,\tau} = |\ SPECIALIZATION_{i,s,\tau} - SPECIALIZATION_{j,s,\tau}\ |$ where states' specializations (which incorporate both direct and indirect exposures) are defined as of the year τ of *effective* banking deregulation of state-pair *i-j*. There are different ways to incorporate this difference in specialization into our tests. One possibility is to run a version of Eq. (3) in which $DEREGULATED_{i,j,t}$ is interacted with indicator variables $HIGH_{i,j,s,\tau}$ and $LOW_{i,j,s,\tau}$ that keep track of whether *i-j-s-t*-level observations are above or below median specialization differences, respectively:

$$\begin{aligned}\Delta\ln(Y_{i,s,t}) - \Delta\ln(Y_{j,s,t}) = {} & \beta_1 L1.DEREGULATED_{i,j,t} \times HIGH_{i,j,s,\tau} \\ & + \beta_2 L1.DEREGULATED_{i,j,t} \times LOW_{i,j,s,\tau} + \delta_{i,j,s} \\ & + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}\end{aligned} \tag{4}$$

An alternative is to run another modified version of Eq. (3) in which $DEREGULATED_{i,j,t}$ is interacted with $\Delta SPECIALIZATION_{i,j,s,\tau}$:

$$\begin{aligned}\Delta\ln(Y_{i,s,t}) - \Delta\ln(Y_{j,s,t}) = {} & \beta_1 L1.DEREGULATED_{i,j,t} + \beta_2 L1.DEREGULATED_{i,j,t} \\ & \times \Delta SPECIALIZATION_{i,j,s,\tau} \\ & + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}\end{aligned} \tag{5}$$

where all of the variables are as defined above.[23]

One weakness of Equations (3) through (5) is that $DEREGULATED_{i,j,t}$ cannot take into account the actual banking integration that takes place. To remedy this problem, in a second set of regressions we replace $DEREGULATED_{i,j,t}$ with the actual banking integration ($INTEGRATION_{i,j,t}$) between a state-pair over time:

$$\Delta\ln(Y_{i,s,t}) - \Delta\ln(Y_{j,s,t}) = \beta_1\ L1.INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t} \tag{6}$$

where, $INTEGRATION_{i,j,t}$ is as defined in 3.3 above. As in the case of Eqs. (4) and (5), we also estimate versions of Eq. (6), in which we interact $INTEGRATION_{i,j,t}$ with $HIGH_{i,j,s,\tau}$ and $LOW_{i,j,s,\tau}$ difference in specialization, or simply with $\Delta SPECIALIZATION_{i,j,s,\tau}$.

However, equations above could still suffer from a number of

[21] We do not weight integration indexes for state-pairs *i-k* and *i-l* before adding them to the one between *i-j*.

[22] In our discussion, we rely on state-pair *i-j* solely for the ease of exposition: as described in Section III.B, our specialization measure *does* take into account both direct (state *i*- or *j*-level) specialization effects as well as indirect ones (due to MBHCs headquartered *i* or *j* owning banks, having presence in states *k, l*, etc.)

[23] Note that the stand-alone $\Delta SPECIALIZATION_{i,j,s,\tau}$ is absorbed into the state-pair-industry fixed-effect since $\Delta SPECIALIZATION_{i,j,s,\tau}$ is fixed as of the date of effective state-pair deregulation τ and does not change over time.

estimation problems. First, banking integration can be endogenous to manufacturing sectors' growth differentials. To deal with this potential problem, we run Eq. (6) and its variations using IV estimation, as explained above in Section 3.1.

Besides endogeneity, we face two additional and related empirical challenges. One potential concern is mean-reversion in our dependent variable (difference in state-pair-industry growths). Relatively smaller industries in a state (i.e., the ones in which the state is more likely to be less specialized) might grow much faster than the larger ones (i.e., sectors in which the state is more likely to be more specialized). More established industries (the ones in which a state is highly specialized) might eventually stagnate and experience slower or even negative growth. One way to account for the potential mean-reversion, which is mainly associated with the different growth cycles of the same industry in different states, is to use another (contemporaneous or lagged) variable that is indicative of the segment's size in the state's economy. One such control variable is the value-added share of the industry (as in Cetorelli and Gambera, 2001, or Cetorelli, 2004), another is its labor share (as in Cetorelli and Strahan, 2006). However, in our case the dependent variable is the difference state-pair-industry-level growths, which is likely to be affected by the state-pair differences in value added or labor share of the sector.[24] Put differently, industry value added or labor share are likely to be endogenous to the growth of that segment, and this, even if we take differences of these variables across state-pairs for a given industry. The second concern that we face is the potential persistence in the difference of growth of sector in a state-pair. For example, introducing lagged state-pair differences in labor share of the segment as a control variable to handle mean reversion would provide little relief if the sector-level growth measures are persistent. In other words, we could face concerns that are due to the dynamic panel nature of our study. As a result, in some of our regressions we use the lags of our dependent variables to control for mean-reversion and persistence to check the robustness of our results. The numbers of lags of the dependent variable that are introduced, are defined by the tests conducted using the system version of Arellano-Bond (AB) regressions that we also run.[25]

3.5. The data

We rely on three separate data sources. First, we aggregate DealScan syndicated loan data at the bank-headquarter state i and sector s to calculate lending specialization indexes to test for the presence of the economic mechanism that lies at the heart of our hypothesis. Second, we use annual BEA estimates of state-and-industry output variables. The BEA value-added estimates (based on industry-level U.S. census), which are the only publicly available state-industry-year level data, help us assess the overall economic impact of banking integration on 19 industrial segments.[26] Third, we use year-end commercial bank and bank holding company financial statements (the so-called Call Reports and Y-9 forms), which which all U.S. banks and BHCs have to file with their federal regulators to calculate the banking integration variable across state-pairs.

We use 1987–1997 DealScan data to calculate $Lending\_Specialization_{i,s,t}$, for which we require to have more than 150 state-sector-year level observations in order to avoid having too many zeros.[27] Intra-state ("home"-state) $Lending\_Specialization_{i,s,t}$ is calculated based on loans in which banks participating in a given syndicate *and* the non-financial corporations receiving the related loan are head-quartered in the same state i. Inter-state (out-of-state) $Lending\_Specialization_{i,s,t}$ is calculated based on syndicated lending in which the non-financial corporations receiving the related credit are head-quartered in states other than the state i in which the banks participating in the syndicate are head-quartered.

We use 1977–1997 BEA data to estimate our regression equations over 1981–1997 (the difference is due to the lags that we introduce in some regressions). We start in 1981 for two reasons. First, we do not have BHC structure (i.e., membership) data prior to 1981.[28] Second, even though Maine was the first state to deregulate bank-entry into its market in 1978, its actual (effective) deregulation did not start until 1982 when New York reciprocated. Third, we take into account the IBBEA, which took effect in September of 1995. This act leveled the playing field in interstate banking at the federal level (i.e., for all states) by allowing banks to consolidate their activities into a single corporate charter and allowing them to enter new markets by acquiring new banks in any state or by opening new branches in the states that allowed interstate branching.[29] Finally, we cannot go beyond 1997 because of changes in the industry classification standards.[30]

In Table 1, we provide information on the manufacturing industries, their distribution as under- and over-specialized sectors of activity across states, as well as their external finance dependence status for the

[24] This issue is not a primary concern for the cited papers. The empirical analysis in Cetorelli and Gambera (2001) is cross-sectional (and does not have a time-series component). In Cetorelli (2004) and Cetorelli and Strahan (2006) the dependent variable is the (level of) number of firms or average firm size in an industry: it is not obvious that a (relative to the rest of the economy) stagnating industry's number of firms or average firm size would shrink as the overall economy continues to expand on average.

[25] When using the system-AB estimator (following Arellano and Bover, 1995, and Blundell and Bond, 1998), we need to (i) select the autoregressive lag structure J and (ii) decide on the number of instruments to use for the lagged dependent variable. The different output measures that we use as dependent variables exhibit empirically different autoregressive patterns. To accommodate such differences, we make use of the AB serial autocorrelation tests applied to the residuals in the differenced equations. As a rule, we use the specifications with the minimum number of lags and with AB-autocorrelation test p-values that do not reject the null hypothesis of no serial correlation at least at the 10%-level for up to second-order serial correlation. We use the system-GMM as in a horse race of methods used in estimating dynamic panel models used in corporate finance research with panel data, Flannery and Hankins (2013) recommend it for practical applications over alternative estimators. Applications of the system-GMM in similar literature include inter alia Beck, Levine, and Loayza (2000), Levine, Loayza and Beck (2000) or Bruno and Hauswald (2014).

[26] An alternative source of data, available from the Annual Survey of Manufacturing (ASM), proved to be unsuitable for our investigation. First, the publicly available version of ASM contains too many zeros (due to non-disclosure rules that require that data be suppressed if they were to reveal or hint at the identity of the participating firms) introducing gaps in a panel setting, something that severely limits the sample size that we could investigate. Second, the ASM data start in 1982 (in contrast to BEA data that start in 1963). These two features matter, especially when the estimation requires dynamic panel techniques with lagged variables as instruments.

[27] As indicated in the next, our main tests are conducted with BEA data over 1981-1997. DealScan dataset does not allow us to have the same coverage: DealScan dataset starts in 1984, but we discard pre-1987 data as they contain less than 50 state-sector-year observations for 1984, 1985, and 1986.

[28] Even though the individual bank financial (the so-called Call Report) data are publicly available since 1978, the BHC (Y-9) data are publicly available starting with 1986 only. We supplement the latter with the so-called BHC structure (membership) data for 1981-1985 that we obtained from the Federal Reserve Board of Governors. We could not find BHC structure data for years prior to 1981.

[29] IBBEA allowed states to opt out of interstate branching for a limited number of years. Many states decided to opt out and restricted this route of expansion by out-of-state banks (e.g., Rice and Strahan, 2010).

[30] In 1997 the U.S. Census Bureau (and hence the BEA) have switched from the Standard Industry Classification (SIC) to the North American Industrial Classification System (NAICS). Even though there is a concordance table between the two systems at the four-digit level, there is no way to match these two classifications at the two-digit level, which is the detail level for the publicly available version of the BEA data that we use.

Table 1

Industry Characteristics. Specialization is defined as the ratio of that sector's share of manufacturing output (i.e., value added) in a given state to that same sector's share of overall U.S. manufacturing output. An under-specialized (over-specialized) industry would have a ratio less (higher) than one. In columns (7) through (10), 1 represents industries that have one of the following characteristics above the median of the sample: *EFD* refers to external finance dependent sectors defined as in Rajan and Zingales (1998); *PPE/TA* is the BEA's sector-level Plant, Property, and Equipment to Total Assets ratio; *Patents* is the sector-level aggregated value of the "xi" variable in Kogan et al. (2017), which is based on the stock price reactions to individual patent announcements; *Risk (SW-Beta)* is the industry-level equally weighted average of Scholes-William CAPM beta. In column (11), 1 indicates those sectors that produce durables.

Industry Name	Bureau of Economic Analysis (BEA) industry ID	2-Digit SIC match	# of states in which the industry is among the under-specialized sectors	# of states in which the industry is among the over-specialized sectors	States in which the industry is among top-three over-specialized sectors	1 if HIGH EFD	PPE/ TA	Patents	Risk (SW-Beta)	Durable Good Producing
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Lumber and wood products	14	24	24	24	AR, ID, ME, MS, MT, OR, VA, VT, WA, WY	0	1	0	0	1
Furniture and fixtures	15	25	33	15	MI, MS, NC, VA	0	0	0	0	1
Stone, clay, and glass products	16	32	24	24	NV, PA, OK, WV	1	1	1	0	1
Primary metal industries	17	33	32	16	IN, MD, OH, PA, WV	0	1	1	0	1
Fabricated metal products	18	34	36	12	CT, IL, MI	0	0	0	0	1
Industrial machinery and equipment	19	35	30	18	IA, NH, WI	1	0	1	1	1
Motor vehicles and equipment	21	371	40	8	DE, IN, KY, MI, OH	0	0	1	1	1
Other transportation equipment	22	372–379	34	14	AZ, CT, FL, KS, MO, WA	0	0	1	1	1
Miscellaneous manufacturing	24	39	31	17	MA, NJ, NV, RI, SD	1	0	0	1	1
Food and kindred products	26	20	25	23	IA, ID, ND, NE	0	1	1	1	0
Textile mill products	28	22	40	8	AL, GA, NC, RI, SC, VA	1	1	0	0	0
Apparel and other textile products	29	23	32	16	NC, NY	0	0	0	0	0
Paper and allied products	30	26	30	18	AL, GA, ME, MN, OR, WA, WI	0	1	1	1	0
Printing and publishing	31	27	29	19	FL, NV, NY	0	0	0	0	0
Chemicals and allied products	32	28	33	15	DE, LA, NJ, WV	1	1	1	1	0
Petroleum and coal products	33	29	33	15	LA, MS, MT, OK, TX, WY	1	1	1	1	0
Rubber and misc. plastics products	34	30	26	22	IA, OK	1	1	0	0	0
Leather and leather products	35	31	30	18	CO, MA, ME, MO, NH, RI, WI	1	0	0	0	0
Electronic equip. and instruments	76	36 & 38	33	15	AZ, CA, VT	1	0	1	1	1
Average			31.3	16.7						

whole sample. The first three columns of Table 1 list the names of the 19 manufacturing industries covered in the study, their BEA identifiers as well as the corresponding two- (or three-) digit SICs, respectively. In columns (4) and (5) of Table 1, we observe that an industry is classified as under-specialized (over-specialized), i.e., with a specialization index below (above) one, in 31.3 (16.7) states on average. In column (6), we list the states in which each industry is among the top-three most specialized sectors.

In the last five columns of Table 1, we indicate if industries are above (with a 1) or below (with a 0) the median characteristic listed in the columns. We later use these characteristics to better understand (to the extent possible with the aggregated data) the underlying economic mechanisms that might be driving our main results (see Section 4.3 below as to how these variables are related with potential mechanisms we have in mind). *EFD* is external finance dependence as proposed by Rajan and Zingales (1998).[31] *PPE/TA* is plant property and equipment to total assets ratio. *Patent Value* is the sector-state-year-level aggregated "xi" variable from Kogan et al. (2017), which is based on stock price reactions to patent announcements. *Industry Risk* is the equally weighted average of listed firms' Scholes-William CAPM betas (which take into account infrequent trading of smaller stocks) as of deregulation date for the state-pair. *Durables* traces durables producing industries.

[31] To do this, we use firm-level variables in COMPUSTAT universe and compute the average value of each firm's external financing needs for 1982-1995, which is calculated by subtracting cash flows from operations from total capital expenditures and then dividing it by total capital expenditures. Next, we aggregate the firm-level ratios of external financial dependence using the median value for all firms in each BEA industrial classification category.

Table 2
Descriptive Statistics. The data come from the BEA Regional Economic Accounts data between 1981 and 1997, which cover 48 contiguous U.S. states (Alaska, Hawaii, and the District of Columbia are excluded) and 19 manufacturing industries at two-digit SIC level. *SPECIALIZATION* is the twice weighted-average of state-industry-level *Specialization* where the MBHC-level weights for each state head-quartered MBHC accounts for its presence in other states, and the state-level weights aggregate MBHC-level specialization at the state-level. The subcomponent *Specialization* is defined as the ratio of that sector's share of manufacturing output (i.e., value added) in a given state to that same sector's share of overall U.S. manufacturing output. $DEREGULATED_{i,j,t}$ is an in indicator variable that is equal to 1 starting with the year of (and including all the subsequent years) the state-pair *i-j* effectively opens their markets to each other's banks, and 0 otherwise. $INTEGRATION_{i,j,t}$ is based on the common banking assets belonging to MBHCs headquartered in either of the two states *i* and *j* in a given year *t,* and takes into all tertiary bank links that states *i* and *j* might have through these MBHCs' banks in other states *k, l,* etc. $INTEGRATION_{,j,t}$ is instrumented following Goetz et al. (2016). The growth of industry-level output measure *Value Added (VA)* is the contribution of an industry to gross state product. (GSP), is defined as $\Delta \ln(Y) = \ln(Y_t) - \ln(Y_{t-1})$. The dependent variable $(\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t}))$ is the differential growth of output variable (Y) of sector *s* in state *i* and year *t relative* to the growth of the same sector *s* in state *j* and year *t*, with *i* (*j*) being the less (more) specialized state of the pair in sector *s* as of the date of effective interstate deregulation for state pair *i-j*.

Dataset of Origin	Num. of obs.	Mean	Std. Dev.	Min.	Max.
BEA					
$SPECIALIZATION_{i,s,\tau}$	300,492	0.69566	0.29119	0.21295	2.21713
$SPECIALIZATION_{j,s,\tau}$	300,492	1.16877	0.43747	0.22406	2.35544
$\Delta SPECIALIZATION_{i,j,s,\tau}$	300,492	0.47310	0.39227	0.00002	2.08136
$\Delta ln(VA_{i,s,t})$	297,632	0.05560	0.17861	−1.54045	1.78398
$\Delta ln(VA_{j,s,t})$	299,408	0.05570	0.16250	−1.54045	1.75786
$\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$	296,609	−0.00001	0.21940	−2.20385	1.94591
Call Reports					
$L1.DEREGULATED_{i,j,t}$	300,492	0.40350	0.49060	0	1
$L1.INTEGRATION_{i,j,t}$	300,492	0.02063	0.06199	0	0.67941

Table 2 provides the summary statistics for the main variables that we use.[32] The average of $SPECIALIZATION_{i,s}$ (for the under-specialized state in the pair *i-j*) is equal to 0.70 with a standard deviation of 0.29, while that of $SPECIALIZATION_{j,s}$ (for the over-specialized state in the pair i-j) is equal to 1.17 with a standard deviation of 0.44. The average of *ΔSPECIALIZATION* is equal to 0.47 and has a standard deviation of 0.39, which suggests that at the *i-j-s* level, as of the date of effective deregulation date τ between *i-j*, there is a lot of variation in industry specialization, which is important for us to be able to tests of our hypothesis. We don't want our empirical results to be driven by accentuated growth patterns of less specialized industries in some states (for example, 50% increase the output by the sole producer in the state would lead to a 50% growth for that sector) or highly specialized industries in other states (these are more likely to be small and economically undiversified states). To avoid such cases, we trim the data based on specialization: We leave out 5% of most- and least-specialized state-industries on either end of *SPECIALIZATION*.[33] To have a proper panel without missing observations, we keep only state-pair-industry observations for which we have no missing values over 1981–1997.[34]

In Table 2, we observe little difference in annual output growths at the state-industry level. For example, the average for $\Delta ln(VA_{i,s,t})$ for the under-specialized state *i* is equal to 0.0556 (i.e., 5.56%) and the average for $\Delta ln(VA_{j,s,t})$ for the over-specialized state *j* is 0.0557 – there is no indication that either type of industries grows faster in the data on average. Unsurprisingly, the average of our dependent variable, the differential output growths $(\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t}))$, is close to zero (–0.00001) and we cannot reject the hypothesis that the difference in VA growth is equal to zero at the 10% level. The standard deviation, minimum and maximum growth rates are also similar across the two groups. On average, thus, there is no evidence that under-specialized industries have disparate growth patterns from over-specialized ones in a state-pair – e.g. there is no apparent mean reversion. Next, we discuss our main results, which are presented in Tables 3 through 5.

4. Findings

4.1. Testing for the economic mechanism underlying our hypothesis

In Table 3, we estimate versions of Eq. (2) to examine whether there is a link between industry-specialization of banks' lending and the industry-specialization of the state in which these financial institutions are headquartered.[35] In columns (1) and (2) of Table 3, we use cross-sectional state-sector-level lending specialization indexes based on *within-state* (i.e., the banks and corporations in the syndicate are headquartered in the same state) lending data that are aggregated over 1987–1997. In column (1) there are no fixed-effects, in column (2) we add state *i* and sector *s* fixed effects to rule out the possibility that our results are driven by state- or sector-level unobservables. The coefficient estimate for *Industrial_Specialization* is equal to 1.8274 in column (1) and 1.7427 in column (2), and both are statistically significant at the 1%-level when standard errors are clustered at the state level. In columns (3) and (4) we repeat the exercise with state-sector-year-level data using pooled-OLS regressions, but now we add state-, sector- and year-fixed effects in column (4). The coefficient estimates are roughly equal to 2.7 in columns (3) and (4), both are statistically significant at the 1%-level. These results suggest that banks' intra-state syndicated lending specialization is highly correlated with their "home"-state's industrial specialization. This is not very surprising as syndicated credit involve large loans made to large corporations, which are likely to be operating in the industries that are dominant in the state. Nevertheless, we find that, at least in the syndicated loan data, banks' are likely to provide in-state credit to those sectors in which their state is specialized in.

In Table 3 columns (5) through (8) we examine to what extent the inter-state (i.e., out-of-bank-headquarter state) syndicated lending of banks is related with their home-state's industrial specialization. This test, however imperfect due to partial coverage provided by DealScan of banks' overall lending, goes to the heart of the mechanism we have in mind when testing our hypothesis. In columns (5)-(8) the inclusion of fixed-effects follow the same pattern as in columns (1)-(4). We focus on the results in columns (6) and (8) that control for potentially confounding factors at the state-, sector- or year-level. In the cross-sectional regression of column (6), the coefficient estimate for *Industrial_Specialization* is equal to 1.8056 and marginally statistically significant at the 10%-level. In the panel regression of column (8), the coefficient estimate for *Industrial_Specialization* is equal to 0.3066 and now statistically

[32] Summary statistics for the variables used in tests (presented in Table 3) for the economic mechanism that underlies our hypothesis are presented in Appendix Table A1. We do not discuss them here for the sake of brevity.

[33] Note that we do *not* trim data based on output growth, something that could bias our results.

[34] The gaps in the data are due to zeros or values that are unreported by the BEA for various reasons.

[35] In these tests we do not take into account banks' presence in other states (markets) as we do in our main tests, because we cannot link DealScan bank identifiers with Call Report bank identifiers. We also carry this analysis at the state-sector or state-sector-year level, as bank-sector or bank-sector-year level data would be overwhelmingly composed of zeros.

Table 3
Correlation between banks' syndicated lending specialization over industries and their home (headquarter) states' industrial specialization. This table presents the OLS estimates for $Lending\_Specialization_{i,s} = \beta \times Industrial\_Specialization_{i,s} + \delta_i + \delta_s + e_{i,s}$ in columns (1), (2), (5) and (6), and $Lending\_Specialization_{i,s,t} = \beta \times Industrial\_Specialization_{i,s,t} + \delta_i + \delta_s + \delta_t + e_{i,s,t}$ in columns (3), (4), (7) and (8). Intra-state (inter-state) sample of columns (1)-(4) (columns (5)-(8)) is defined by both banks participating in the syndicate and the borrower non-financial firm are head-quartered in the same state (in different states). $Lending\_Specialization_{i,s}$ is the share of syndicated loans made to sector *s* compared to all 19 BEA industries by banks headquartered in state *i* between 1987 and 1997 divided by the share of all US syndicated loans made to industry *s* by all banks in the sample during the same period. $Lending\_Specialization_{i,s,t}$ is similarly defined but for each one of the years *t* between and including 1987 and 1997. DealScan syndicated loan data are aggregated at the sector *s*, bank-headquarter state *i*, and year *t* level. State-sector (state-sector-year) observations are given a value of zero if a particular sector did not receive any syndicated loans in a given state (year), and we eliminate observations if banks headquartered in state *i* have made syndicated loans to less than three sectors each year (in order to avoid inflated lending specialization indexes). $Industrial\_Specialization_{i,s}$ is the ratio of sector *s*'s share of manufacturing output (i.e., value added) during 1987–1997 in a given state *i* to that same sector's share of overall U.S. manufacturing output over the same period. $Industrial\_Specialization_{i,s,t}$ is similarly defined on an annual basis. Fixed effects are indicated by δ with subscripts *i, s,* and *t* refer to state, sector, and year, respectively. The standard errors are clustered at the state (*i*) level in all regressions. *t*-stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Dependent variable:	Intra-state Syndicated Lending aggregated $Lending\_Specialization_{i,s}$ (1)	(2)	annual $Lending\_Specialization_{i,s,t}$ (3)	(4)	Inter-state Syndicated Lending aggregated $Lending\_Specialization_{i,s}$ (5)	(6)	annual $Lending\_Specialization_{i,s,t}$ (7)	(8)
Industrial_Specialization	1.8274 ***	1.7427 ***	2.6945 ***	2.6681 ***	1.8953 *	1.8056 *	0.3378 ***	0.3066 ***
	(4.20)	(4.34)	(5.37)	(5.36)	(1.80)	(1.70)	(3.41)	(3.80)
Level of observations	*i-s*	*i-s*	*i-s-t*	*i-s-t*	*i-s*	*i-s*	*i-s-t*	*i-s-t*
Number of:								
observations	646	646	3515	3515	722	722	4370	4370
industries	19	19	19	19	19	19	19	19
clusters (states)	34	34	29	29	38	38	31	31
Fixed Effects:								
state (*i*)	no	yes	No	yes	no	yes	no	Yes
sector (*s*)	no	yes	No	yes	no	yes	no	Yes
year (*t*)			No	yes			no	yes

Table 4
Effect of pairwise interstate banking deregulation on differential output growth at the state-pair-sector level – Within Regressions. This table presents the *Within* regression estimates for $\Delta\ln(VA_{i,s,t}) - \Delta\ln(VA_{j,s,t}) = \beta \times DEREGULATED_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$. Where present the number of the lags of the dependent variable are determined using a system-Arellano-Bond estimator. $\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$ is the differential growth of the *Value Added (VA)* of sector *s* in state *i* and year *t relative* to the growth of the same sector *s* in state *j* and year *t*, with *i* (*j*) being the less (more) specialized state of the pair in sector *s* as of the date of effective interstate deregulation for state-pair *i-j*. $DEREGULATED_{i,j,t}$ is an indicator variable that is equal to 1 starting with the year (including all the subsequent years) in which the state-pair *i-j* effectively opens their markets to each other's banks, and 0 otherwise. *ΔSPECIALIZATION* is the difference specialization of sector *s* across states *i* and *j* as of date *t*; and it is based on *Industrial_Specialization*, which is the ratio of a sector's share of manufacturing output (i.e., value added) in a given state to that same sector's share of overall U.S. manufacturing output. *SPECIALIZATION* is the twice weighted-average of state-industry-level *Industrial_Specialization* where the MBHC-level weights for each state head-quartered MBHC accounts for its presence in other states, and the state-level weights aggregate MBHC-level specialization at the state-level. *HIGH* (*LOW*) is an indicator variable that equals 1 if *ΔSPECIALIZATION* > (<) industry median, and 0 otherwise. All regressions include state-pair-sector, state i-year, state j-year, sector-year, and year fixed-effects. *Lt* represents the t^{th} lag. The standard errors are clustered at the *i-j-s* level. *t*-stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	***Basic Model* (1)**	***With Lags* (2)**	**Above (*HIGH*) & Below (*LOW*) of Median (*ΔSPECIALIZATION*) (3)**	***Interaction with ΔSPECIALIZATION* (4)**
L1.DEREGULATED	0.0146 ***	0.0144 ***		0.0077 ***
	(7.53)	(6.95)		(3.55)
L1.DEREGULATED × HIGH			0.0202 ***	
			(9.49)	
L1.DEREGULATED × LOW			0.0094 ***	
			(4.47)	
L1.DEREGULATED × ΔSPECIALIZATION				0.0152 ***
				(6.94)
L1.[Δln(Y_{i,s,t}) – Δln(Y_{j,s,t})]		−0.0911 ***		
		(26.94)		
L2.[Δln(Y_{i,s,t}) – Δln(Y_{j,s,t})]		−0.0638 ***		
		(23.58)		
L3.[Δln(Y_{i,s,t}) – Δln(Y_{j,s,t})]		−0.0707 ***		
		(25.84)		
Number of observations	293,403	293,403	293,403	293,403
Number of clusters	17,259	17,259	17,259	17,259
H_0: equality of coeff. estimates (Chi^2-test)			41.0 ***	

Table 5
Effect of pairwise interstate banking deregulation on differential output growth with specialization difference – IV Regressions. This table presents *IV* estimates for $\Delta\ln(VA_{i,s,t}) - \Delta\ln(VA_{j,s,t}) = \beta \times INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$. Where present, the number of the lags of the dependent variable are determined using a system-Arellano-Bond estimator. $\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$ is the differential growth of the *Value Added (VA)* of sector *s* in state *i* and year *t relative* to the growth of the same sector *s* in state *j* and year *t*, with *i* (*j*) being the less (more) specialized state of the pair in sector *s* as of the date of effective interstate deregulation for state-pair *i-j*. $INTEGRATION_{i,j,t}$ is based on the common banking assets belonging to MBHCs headquartered in either of the two states *i* and *j* in a given year *t*, and takes into all tertiary bank links that states *i* and *j* might have through these MBHCs' banks in other states *k, l*, etc. $INTEGRATION_{,j,t}$ is instrumented following Goetz et al. (2016). *ΔSPECIALIZATION* is the difference of specialization of sector *s* across states *i* and *j* as of date *t*, based on *Industrial_Specialization*, which is the ratio of a sector's share of manufacturing output (i.e., value added) in a given state to that same sector's share of overall U.S. manufacturing output. *SPECIALIZATION* is the twice weighted-average of state-industry-level *Industrial_Specialization* where the MBHC-level weights for each state head-quartered MBHC account for its presence in other states, and the state-level weights aggregate MBHC-level specialization at the state-level. *HIGH* (*LOW*) is an indicator variable that equals 1 if *ΔSPECIALIZATION* > (<) industry median, and 0 otherwise. Regressions have state-pair-sector, state *i*-year, state *j*-year, sector-year, and year fixed-effects. *Lt* represents the t^{th} lag. Standard errors are clustered at the *i-j-s* level. *t*-stats are below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, 1% levels, respectively.

	Basic Model (1)	*With Lags* (2)	Above (*HIGH*) & Below (*LOW*) of Median (*ΔSPECIALIZATION*) (3)	*Interaction with ΔSPECIALIZATION* (4)
L1.INTEGRATION	0.1669 ***	0.1897 ***		0.0428
	(4.46)	(4.54)		(0.92)
L1.INTEGRATION × *HIGH*			0.3112 ***	
			(5.65)	
L1.INTEGRATION × *LOW*			0.0924 **	
			(2.28)	
L1.INTEGRATION × *ΔSPECIALIZATION*				0.3753 ***
				(3.55)
$L1.[\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})]$		−0.0911 ***		
		(26.92)		
$L2.[\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})]$		−0.0639 ***		
		(23.63)		
$L3.[\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})]$		−0.0709 ***		
		(25.85)		
Number of observations	293,403	293,270	293,403	293,403
Number of clusters	17,259	17,259	17,259	17,259
Under-identification test	1022.2 ***	1021.1 ***	626.8 ***	347.9 ***
Weak instruments test	1399.2 ***	1397.0 ***	438.1 ***	226.7 ***
H_0: equality of coeff. estimates (Chi^2-test)			15.5 ***	

significant at the 1%-level. These results suggest that there is a strong positive correlation between the sector-specialization of banks' out-state-lending and the industrial specialization of these institutions' headquarter states. These tests provide an incomplete picture of the banks' overall lending behavior, as DealScan data only cover large syndicated loans. Nevertheless, these are the only ones that we can conduct with publicly available data support the economic mechanism that we have in mind for our hypothesis. Armed with this finding, next we turn our attention to the tests of our hypothesis: whether banks' exposure to the predominant industries in the markets in which they are present helps the growth of the same sector in the new markets that these institutions enter.

4.2. Main results

In Table 4, we provide the *Within* regression estimates of Eq. (3) in its various versions. In column (1), the coefficient estimate β_1 of *L1. DEREGULATED* in the basic version of Eq. (3) is equal to 0.0146, which is statistically significant at the 1%-level. This finding suggests that, after interstate bank-entry deregulation, industries in states that are less-specialized in them (denoted *i*), compared to the same sectors located in states (denoted *j*) that are more specialized in them, grew 1.46% faster, on average. We obtain a very similar result in column (2) when we add lagged dependent variables to control for the dynamic panel nature of our setup: the coefficient estimate β_1 is equal to 0.0144 and statistically significant at the 1%-level. In column (3), we present the estimates of Eq. (4) in which we interact *L1.DEREGULATED* with the indicator variables *HIGH* (*LOW*) that trace whether observations are above (below) the median of *ΔSPECIALIZATION* (which is 0.37). The coefficient estimate for *L1.DEREGULATED* × *HIGH* is equal to 0.0202, the one for *L1.DEREGULATED* × *LOW* is equal to 0.0094, both of which are statistically significant at the 1%-level. Importantly, the implicit difference of 1.08% between these two coefficient estimates is statistically significant at the 1%-level in a Chi^2 test. This result suggests that the state-pair-sector value-added grows twice as fast on average for the sample for which *ΔSPECIALIZATION* is above its median: higher the difference in sector specific specialization between local banks and entering institutions, higher is the observed growth. This finding is further corroborated in column (4) of Table 4, in which we present the estimates of Eq. (5). The coefficient estimate for *L1.DEREGULATED* is equal to 0.0077, the one for *L1.DEREGULATED* × *ΔSPECIALIZATION* to 0.0152, both of which are statistically significant at the 1%-level. These coefficient estimates suggest that, while under-developed industries' growth in states increases after deregulation of bank entry, it goes up much faster after deregulation to states with banks that have increased expertise in lending to the same sectors.

Given the potential endogeneity concerns indicated in Section 3.1, in the rest of the paper we focus on Eq. (6) and its variants estimated using the IV-regressions. Our main IV results are presented in Table 5, which has the same format as Table 4. In column (1), the coefficient estimate for *L1.INTEGRATION* is equal to 0.1669 and statistically significant at the 1%-level: a one standard deviation increase in integration (which is equal to 0.0620) with a state in which banks have expertise in the sector generates a 1.03% (= 0.1669 × 0.0620 × 100) higher growth for the under-developed sector. This finding, which takes into account the potential endogeneity of banking integration, is in line with the 1.46% we observe in column (1) of Table 4. We obtain a similar result in column (2) when we take the dynamic panel nature of the model into account – the coefficient estimate for *L1.INTEGRATION* is equal to 0.1897 and statistically significant at the 1%-level when we use the Arellano-Bond estimator: a one-standard deviation increase in integration with a state in which banks have higher lending experience in the sector generates a 1.18% (= 0.1897 × 0.0620 × 100) higher growth for the under-developed sector. In column (3), we split the equivalent of Eq. (4) for the

Table 6

Exploration of the underlying economic mechanisms – IV Regressions. This table presents *IV* estimates for $\Delta\ln(VA_{i,s,t}) - \Delta\ln(VA_{j,s,t}) = \beta \times INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$. Where present, the number of the lags of the dependent variable are determined using a system-Arellano-Bond estimator. $\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$ is the differential growth of the *Value Added (VA)* of sector *s* in state *i* and year *t relative* to the growth of the same sector *s* in state *j* and year *t*, with *i* (*j*) being the less (more) specialized state of the pair in sector *s* as of the date of effective interstate deregulation for state-pair *i-j*. $INTEGRATION_{i,j,t}$ is based on the common banking assets belonging to MBHCs headquartered in either of the two states *i* and *j* in a given year *t*, and takes into all tertiary bank links that states *i* and *j* might have through these MBHCs' banks in other states *k, l*, etc. $INTEGRATION_{,j,t}$ is instrumented following Goetz et al. (2016). *ΔSPECIALIZATION* is the difference of specialization of sector *s* across states *i* and *j* as of date *t*, and it is based on *Industrial_Specialization*, which is the ratio of a sector's share of manufacturing output (i.e., value added) in a given state to that same sector's share of overall U.S. manufacturing output. *SPECIALIZATION* is the twice weighted-average of state-industry-level *Industrial_Specialization* where the MBHC-level weights for each state head-quartered MBHC accounts for its presence in other states, and the state-level weights aggregate MBHC-level specialization at the state-level. *HIGH* (*LOW*) is an indicator variable that equals 1 for which the industry characteristic is above its median. *EFD* refers to external finance dependent sectors defined as in Rajan and Zingales (1998); *PPE/TA* is the BEA's sector-level Plant, Property, and Equipment to Total Assets ratio; *Patents* is the sector-level aggregated value of the "xi" variable in Kogan et al. (2017), which is based on the stock price reactions to individual patent announcements; *Risk (SW-Beta)* is the industry-level equally weighted average of Scholes-William stock return beta. All regressions include state-pair-sector, state i-year, state j-year, sector-year, and year fixed-effects. *Lt* represents the tth lag. The standard errors are clustered at the *i-j-s* level. *t*-stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, 1% levels, respectively.

Panel A: High- versus Low-Characteristics										
Characteristic =	***EFD***		***PPE/ TA***		***Patents***		***Industry Risk (SW-Beta)***		***Durables (HIGH) versus Non-durables (LOW)***	
	(1)		***(2)***		***(3)***		***(4)***		***(5)***	
L1.INTEGRATION × HIGH	0.2199	***	0.1195	**	0.2142	***	0.2377	***	0.2577	***
	(3.59)		(2.15)		(3.54)		(4.16)		(4.59)	
L1.INTEGRATION × LOW	0.1246	**	0.2040	***	0.1128	**	0.1117	***	0.0515	
	(2.29)		(3.52)		(2.15)		(2.61)		(0.89)	
Number of observations	293,403		293,403		293,403		293,403		293,403	
Number of clusters	17,259		17,259		17,259		17,259		17,259	
Under-identification test	642.5	***	626.7	***	646.2	***	455.1	***	639.9	***
Weak instruments test	384.8	***	374.4	***	386.8	***	298.1	***	384.1	***
H_0: equality of coeff. estimates (Chi^2-test)	1.2		1.0		1.4		3.7	**	5.7	**
Panel B: High- versus Low-Characteristic Groups for the *Above* the Median of *ΔSPECIALIZATION* Subsample										
Characteristic =	***EFD***		***PPE/ TA***		***Patents***		***Industry Risk (SW-Beta)***		***Durables (HIGH) versus Non-durables (LOW)***	
	(1)		***(2)***		***(3)***		***(4)***		***(5)***	
L1.INTEGRATION × HIGH	0.4210	***	0.0466		0.3389	***	0.3383	***	0.4607	***
	(3.68)		(0.47)		(3.33)		(3.32)		(4.45)	
L1.INTEGRATION × LOW	0.1116		0.3968	***	0.1202		0.1699	**	0.0017	
	(1.28)		(4.01)		(1.32)		(2.45)		(0.02)	
Number of observations	146,693		146,693		146,693		146,693		146,693	
Number of clusters	8629		8629		8629		8629		8629	
Under-identification test	245.9	***	243.3	***	255.1	***	190.5	***	259.9	***
Weak instruments test	150.9	***	148.3	***	157.4	***	123.9	***	163.3	***
H_0: equality of coeff. estimates (Chi^2-test)	4.0	**	5.5	**	2.2		2.3		9.5	***
Panel C: High- versus Low-Characteristic Groups for the *Below* the Median of *ΔSPECIALIZATION* Subsample										
Characteristic =	***EFD***		***PPE/ TA***		***Patents***		***Industry Risk (SW-Beta)***		***Durables (HIGH) versus Non-durables (LOW)***	
	(1)		***(2)***		***(3)***		***(4)***		***(5)***	
L1.INTEGRATION × HIGH	0.0797		0.1395	**	0.1401	*	0.1814	***	0.1521	**
	(1.09)		(2.07)		(1.83)		(2.59)		(2.19)	
L1.INTEGRATION × LOW	0.1368	*	0.0874		0.0772		0.0532		0.0539	
	(1.93)		(1.18)		(1.16)		(0.96)		(0.72)	
Number of observations	146,710		146,710		146,710		146,710		146,710	
Number of clusters	8630		8630		8630		8630		8630	
Under-identification test	393.5	***	389.0	***	384.0	***	358.6	***	370.0	***
Weak instruments test	225.8	***	224.7	***	219.8	***	232.2	***	216.9	***
H_0: equality of coeff. estimates (Chi^2-test)	0.3		0.2		0.3		2.5		0.8	

IV-estimator. The coefficient estimate for the *L1.INTEGRATION × HIGH* is equal to 0.3112 (statistically significant at the 1%-level), the one for *L1.DEREGULATED × LOW* is equal to 0.0924 (significant at the 5%-level). The difference of 0.2188 between these two coefficient estimates is statistically significant at the 1%-level in a Chi^2-test: the effect observed in column (1) is mostly driven by the state-pairs for which the difference in *ΔSPECIALIZATION* is above the sample's median. This is consistent with a higher discrepancy between the industry lending-experience of local versus entrant banks leading to a larger the growth for the local under-developed sectors. In the last column of Table 5, the coefficient estimate of the interaction *L1.INTEGRATION × ΔSPECIALIZATION* is equal to 0.3753 and statistically significant at the 1%-level: one standard deviation increase in *INTEGRATION* (which is 0.0620) coupled with a one standard deviation increase in *ΔSPECIALIZATION* (which is 0.3923) leads to a 0.91% (= 0.3753 × 0.0620 × 0.3923 × 100) increase in the growth of the under-developed sector in state *i*, following entry by banks more experienced in lending to that sector. Again, this IV-estimate is in the ballpark of the ones obtained and discussed above.

These main results are consistent with our main hypothesis that industry specific knowledge of banks entering a new lending market matters: the under-developed sectors in the state into which banks (with higher knowledge of the sector) enter grow faster by roughly 1% per year, after controlling with as many unobservables as we possibly can, given the aggregated data that are at our disposal. The industry-specific knowledge that is transmitted through MBHC-networks appears to have an impact on the real sector integration across regions.

Could the above results be mostly due to local banks' reactions (in terms of lending) to out-state banks' entry? Put differently, could we be wrongly associating the results to the industry-specialization of entrant banks, when instead they are due to local banks' responses to the opening of their state's banking market to MBHCs from other states? Unfortunately, it is impossible for us to respond to these questions empirically given the lack of bank-industry-level or even industry-state-level lending data for the U.S. As a result, we draw from the existing research to argue that local banks' reactions cannot explain our main results. First, Evanoff and Ors (2008) find that, after the same interstate banking deregulations, and in the face of out-of-state entry (through the acquisition of local rivals), *local incumbent* banks make improvements in their productive efficiencies by reducing their costs. We argue that such cost-cutting local banks are highly unlikely to spend additional resources (for ex., hire new loan officers, buy new credit-scoring data or systems in order to cover new sectors) to improve monitoring and increase the lending volume in industries in which they are not proficient. Second, Jiang et al. (2016) find that banks reduce opacity of their financial statements (by reducing discretionary loan loss provisions) in the face of higher competition following interstate banking deregulations. This suggests that local banks are less likely to be able to hide losses that they might incur if they were to lend in sectors that they know less about. Finally, Jiang et al. (2019) find that, following US bank-entry deregulations, banks' liquidity creation suffers, and this, especially so for smaller (hence, plausibly local) banks that face higher competition from the larger MBHCs entering their markets. As a result, we doubt that local banks, which are coping with above-indicated effects of bank-entry deregulation, can increase their volume of lending in sectors on which they have less of a lending expertise. In the next section, we examine the possible channels at play, as much as one can when relying on state-sector level data.

4.3. An investigation of possible channels

Next we explore the possible channels involved in the main results presented above. We do so by examining industry level characteristics on external finance dependence, availability of assets that can be used as collateral when borrowing from banks, value of patents created in an industry, the risk of the industry, and whether the sector can be classified as durables-producing or not. In Table 6, we run IV-regressions akin to that of column (3) of Table 5, with the difference being that now the indicator variable *HIGH* (*LOW*) refers to the part of the sample that above (below) the median for the industry *characteristic* variable.

The first of these sector level characteristics is *EFD* (Table 6, Panel A, column (1)): in line with Goetz and Gozzi (2020) findings, we expect less-developed sectors that rank as high-*EFD* to grow faster upon entry of banks that are specialized in them. The coefficient estimates for the interactions *L1.INTEGRATION* × *HIGH* and *L1.INTEGRATION* × *LOW* are 0.2199 and 0.1246, respectively, both of which are statistically significant at the conventional levels. While this result appears to be consistent with the idea that external finance dependence is one of the possible channels through which prior sector-lending-expertise might matter for our results, the difference of 0.0953 between these estimates is not statistically different in a Chi^2-test.

In column (2) of Table 6, Panel A, we use *PPE/TA* as a proxy for the "soft-information" nature of industries might matter: we expect less-developed sectors in state *i* with lower fractions of assets that can be pledged as collateral for loans (traced by the indicator variable *LOW*) to benefit more from the entry of banks that more knowledgeable in processing their industry's soft-information.[36] The coefficient estimates for the interactions *L1.INTEGRATION* × *HIGH* and *L1.INTEGRATION* × *LOW* are 0.1195 and 0.2040, respectively, both of which are statistically significant at the conventional levels. While the column (2) evidence appears consistent with a channel that incorporates soft-information processing advantaged conveyed by prior industry knowledge before market entry, the difference between 0.1195 and 0.2040 is not statistically significant.

In Table 6, Panel A, column (3), we examine whether under-developed industries of state *i* that developed more valuable patents benefit more from the entry of banks that know their industry better: estimates for the interactions *L1.INTEGRATION* × *HIGH* and *L1.INTEGRATION* × *LOW* are 0.2142 and 0.1128, respectively, both of which are statistically significant at the conventional levels. Yet again, the difference between these estimates is not statistically significant.

In Table 6, Panel A, column (4), we examine whether sectors with above-median industry risk (as reflected in the equally-weighted average of Scholes-William CAPM betas of the listed companies in that sector) benefit more from integration through out-of-state banks that know that sector better.[37] In Table 6, Panel A, column (4), the coefficient estimate for *L1.INTEGRATION* × *HIGH* is equal to 0.2377, whereas the one *L1.INTEGRATION* × *LOW* is equal to 0.1117 (both statistically significant at the 1%-level). The implicit difference of 0.1260 between these two estimates is statistically significant in a Chi^2-test at the 5%-level. These results appear to suggest that MBHCs entering new markets help riskier sectors, in which they happen to have prior knowledge , grow faster. This finding is consistent with the market-entering banks' prior expertise, allowing them to better assess the associated risks. It is also consistent with the possibility that local banks are less willing to offer credit in higher risk sectors because they lack the diversity that the market-entering banks' acquire through geographic expansion (for benefits of geographic diversification of banks, see Goetz et al., 2016). It could also be that riskier industries benefit from credit by entering banks that might be affected by agency problems leading to higher risk taking in MBHCs that expand over the geographic space (e.g., Goetz et al., 2013). Unfortunately, we cannot discern between these stories given the aggregated nature of the data at our disposal. As a result, we leave additional examination of the role of risk and industry-growth to further research.

Finally, in the last column of Table 6's Panel A, we inquire whether previous industry-lending experience helps durables producing sectors (tracked by an indicator variable labeled as *HIGH* to keep the table simple) more that non-durables producing ones (traced by an indicator variable labeled *LOW*). The coefficient estimate for *L1.INTEGRATION* × *HIGH* (to be read as *L1.INTEGRATION* × *DURABLES*) is equal to 0.2577 and statistically significant at the 1%-level, whereas the one for "*L1.INTEGRATION* × *NON-DURABLES*" is not statistically significant. This finding expands those of Damar et al. (2020), who find that households' purchases of durables increase following interstate banking deregulations, which is consistent with a higher provision of financing (consumer credit for durables) by banks. What we observe suggests that under-developed durables sectors can grow faster in meeting the higher

[36] We thank the anonymous referee for proposing this and the next possible channels.

[37] It should be noted that our measure of risk is at the industry-level as of the year of state-pair's effective deregulation (and *not* at the industry-state-year level for lack of listed companies in each of the industries, in each of the states, in each of the years in the CRSP stock returns dataset). We take the equally-weighted average to avoid a measure of risk dominated by the larger listed firms, something that is likely to make our industry-risk proxy even further away from non-listed firm characteristics. We rely on the Scholes-William CAPM Beta as it takes into account less frequent trading of small stocks. Nevertheless, we acknowledge that our risk-measure obtained from the listed firms in an industry may not fully represent the systematic risk of the industry. Moreover, we would like to have a measure of risk that varies at the state-industry-year-level, but the fact that certain industries are not represented in all the states in the universe of listed firms restrains us to use an industry-level risk measure. Despite these weaknesses, we believe that the resulting tests are nevertheless worth pursuing.

demand, if they have access to banks that specialize in their sector (and as such, better assess the associated corporate as well as consumer credit).

Given the suggestive but weak set of results of Panel A (in the sense that the observed coefficient estimate differences across *HIGH* and *LOW* interactions with *EFD, PPE/TA,* and *patent value* are not statistically significant), and wanting to avoid triple interactions, we split the sample into two as above- and below-median of *ΔSPECIALIZATION*. If our conjecture about the role of prior industry knowledge of new-market-entrant banks being important in the growth of under-developed sectors, then the above listed channels should be more apparent for the above-median of *ΔSPECIALIZATION* sample (presented in Panel B of Table 6), and they should be less so for the below-median of *ΔSPECIALIZATION* sample (Panel C of Table 6).

This is indeed the case. In Panel B of Table 6, the coefficient estimates for the *L1.INTEGRATION* × *HIGH* interaction for *EFD, Patents' Value, Industry Risk*, and *Durables* are 0.4210, 0.3389, 0.3383, and 0.4607, respectively, the one for *L1.INTEGRATION* × *LOW* interaction for *PPE/TA* is 0.3968, all of which statistically significant at the 1%-level. Their counterparts (i.e., *L1.INTEGRATION* × *LOW* in columns (1) and (3)-(5), and *L1.INTEGRATION* × *HIGH* in column (2)) are not statistically significant except in column (4) for industry level risk. Moreover, the observed differences among the coefficient estimates is statistically significant in a Chi^2-test for *EFD, PPE/TA*, and *Durables*.

In stark contrast, we observe no such clear pattern in Panel C of Table 6, for the below-median of *ΔSPECIALIZATION* subsample. These findings suggest that our main results are consistent with four possible channels. Prior sector-lending experience matters more when the difference in sector expertise between local and entrant banks is larger for high external finance dependent sectors, sectors that have lower fraction of assets that can be pledged as loan collateral, industry segments whose listed-companies' exhibit higher risk (as reflected in stocks having higher Scholes-William CAPM betas), and sectors that produce durable goods.[38]

4.4. Robustness checks

We conduct a series of checks to see if our findings are robust, the first series of which, we present in Appendix Table A3. First, we examine if our main results with the basic IV-model also hold if we measure VA-growth over longer horizons. The coefficient estimates for *L1.INTEGRATION* for VA-growth over 2-, 3-, and 5-years are 0.3749, 0.3596, and 0.5501 (all statistically significant at the 1%-level) in columns (1) through (3) of Table A3 (compared to 0.1669 in column (1) of Table 5). So, the growth rates that we observe following banking integration are not reverting back to a mean, at least not in the first five years. The observed change appears to hold for the medium term.

In a second test, presented in column (4) of Appendix Table A5, we exclude all states that open-up their banking markets at the national level but non-reciprocally (NNR): the remaining state-pairs are overwhelmingly those that required reciprocity when allowing counterparty states' banks. The column (4) *L1.INTEGRATION* coefficient estimate is 0.2083 (statistically significant at the 1%-level) as opposed to 0.1669 in column (1) of Table 5. We conclude that more liberal deregulation (in the sense that no reciprocity was required) is not driving our results.

In column (5) of Appendix Table A3, we exclude all the state-pairs that involve the five states with the lowest GSPs (namely, MT, NV, ND, SD, WY) as we do not want our results to be driven under-developed sectors of non-industrial small state-economies that are more likely to experience large increases in growth. The column (5) *L1.INTEGRATION* coefficient estimate is 0.1723 (statistically significant at the 1%-level) is very similar to 0.1669 observed in our main results presented in column (1) of Table 5. In column (6) of Appendix Table A3, we exclude all negative growth in VA observations: our results remain unaffected. Finally, in the last column of Appendix Table A3, we exclude post-IBBEA years of 1996 and 1997: yet again our main results remain very similar.

In a further step, we examine the consistency of our estimates by considering the components of value added (gross operating surplus, total compensation to capital, total employment, total wages, and a simple measure of productivity per worker) and estimating models similar to the ones above for each one of them and comparing them within the framework of a very simple model. The resulting (back-of-the-envelope type) estimates comfort us that our empirical approach generates internally consistent estimates (discussed in the Appendix with the associated results presented in Appendix Table A5).

5. Conclusion

We examine whether interregional banking integration could affect industry structure. Identifying banking's effect on the real sector at the industry level is empirically difficult for a number of reasons. First, a change that is exogenous to the industry exposure of banks is needed, as cross-sectional variation is unlikely to be convincing for pinning down the effect of banks' industry-exposures on sector-level growth: many confounding effects would get in the way of establishing causality. Second, even with exogenous changes in regulation, endogeneity is a major challenge, as financial institutions' actual entry decisions in new markets might not be separated from their growth opportunities. Finally, publicly available data provide an incomplete coverage (limited to large syndicated loans) of the industry composition of US banks' loan portfolios.

First, using the publicly available syndicated loan data, we find that banks' provision of credit to in-state large corporations is positively correlated with that state's industrial specialization. More importantly, in support of the mechanism we have in mind for our hypothesis, we find that banks' out-of-state syndicated corporate lending's sector-specialization is positively correlated with the industrial specialization of these financial institutions' home states. This empirical evidence, even if incomplete due to DealScan data's nature, provides empirical support for the economic mechanism underlying our hypothesis.

In our main analysis, we use interstate bank-entry deregulations that took place in the U.S. to identify the effects of banks' prior industry exposure upon entering a new market, on the growth of the same sectors therein. We find robust evidence that is consistent with our conjecture that banking integration affects states' industry structures. Following interstate bank-entry deregulation, as MBHCs, which were over-exposed to certain industries because the states in which they operated were more specialized in them, acquired other institutions in other states, the resulting banking integration led to an increase in the growth of under-developed sectors in these institutions new markets – and hence to more industrial convergence. This finding is in contrast with banking integration simply leading to higher provision of bank finance. Our results strongly indicate that market entering banks' prior industry exposure plays a role in the growth of under-developed industries. The observed effect is more pronounced in industries that are more external finance dependent, have less physical capital that can be pledged as collateral for loans, that are relatively riskier, produce durable goods, yet it is not driven by small states, and persist at least up to five years.

Our results suggest that the industrial landscape is shaped by banks' lending expertise in different industries. As such, our findings are broader than the banking or financial integration literatures. We contribute to the larger research area on finance and growth (e.g., Levine, 1997, 2005), as our findings help us better understand how banks shape growth of sectors in the real economy. The resulting dilemma is not an obvious one for the policymakers: our findings suggest

[38] Both industry patent and risk measures are rather crude. Not all 19 industries have listed companies in each of the 48 states. Moreover, privately held companies' patent values and risk profiles may be weakly correlated with those of their stock market-listed counterparts. As a result, the associated evidence should be viewed with caution.

that governments' and regulators' approval or rejection decisions, for example, on foreign bank entry can have implications beyond the stability of the financial system or growth of the economy. The long-term composition of a country's industries might differ depending on the entering banks' expertise given their sectoral exposures in the countries in which they already operate.

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Appendix

A. consistency check and interpretation through a simple calibration exercise

To check the consistency of the findings in the main text, we further examine the sub-components of *VA* and conduct a simple, partial equilibrium, calculation exercise relying on a representative production function. The two main components of *VA* are *Gross Operating Surplus* (*GOS*), which is the return to the capital employed in the industry at the state level, and *Compensation of Employees* (*COMP*), which is the total of disbursements to industry's employees (including wages plus retirement and similar contributions made by the employers).[39] BEA data also allow us to observe, always at the state-industry level, the total number of full- and part-time employees (*EMP*), which is without a full-time equivalent adjustment, and wages (*WAGE*), which are gross wages and salaries as well as full time and part-time wage and salary employment.[40] For the sake of the decomposition exercise that follows, we calculate productivity (*PROD*) as value added per employee at the state-industry level. The summary statistics for these variables are presented in Table A4.

Our goal is not to conduct a detailed output decomposition, but to have an intuitive benchmark with which we can assess the relative sizes of coefficient estimates with respect to each other given that we have a different number of observations for each of our output variables. With this objective in mind, we define the following constant-returns-to-scale Cobb-Douglas function with capital and labor as the only factors of production:

$$Y = A(K)^{\alpha}(L)^{1-\alpha} \tag{7}$$

where, Y is the output (i.e., value added), A is TFP, K is the capital stock, α is the capital intensity (share) parameter, and L is the labor employed. Imposing standard equilibrium conditions under perfectly competitive markets that marginal products of capital and labor are equal with the return on capital (r) and wages (w), respectively, we rewrite Eq. (7) as:[41]

$$Y = rK + wL \tag{8}$$

Substituting value added for Y, gross operating surplus (i.e., remuneration of capital) for rK, and compensation of labor for wL, Eq. (7) becomes:

$$VA = GOS + COMP \tag{9}$$

Table A1

Summary statistics for the main variables in Table 3. $Lending\_Specialization_{i,s}$ is the share of syndicated loans made to sector s compared to all 19 BEA industries by banks headquartered in state i between 1987–1997 divided by the share of all US syndicated loans made to industry s by all banks in the sample during the same period. $Lending\_Specialization_{i,s,t}$ is similarly defined but for each one of the years t between and including 1987 and 1997. DealScan syndicated loan data used for lending specialization are aggregated at the sector s, bank-headquarter state i, and year t level. State-sector (state-sector-year) observations are given a value of zero if a particular sector did not receive any syndicated loans in a given state (year). We eliminate observations if banks headquartered in state i have made syndicated loans to less than three sectors either over 1987–1997 (for state-sector observations) or each year (state-sector-year) in order to avoid inflated lending specialization indexes. $Industrial\_Specialization_{i,s}$ is the ratio of sector s's share of manufacturing output (i.e., value added) during 1987–1997 in a given state i to that same sector's share of overall U.S. manufacturing output over the same period. $Industrial\_Specialization_{i,s,t}$ is similarly defined on an annual basis.

Dataset of origin	Num. of obs.	Mean	Std. Dev.	Min.	Max.
DealScan					
Intra-State $Lending\_Specialization_{i,s}$	646	1.54613	5.63495	0	93.59828
Intra-State $Lending\_Specialization_{i,s,t}$	3515	2.26035	17.99077	0	746.9541
Inter-State $Lending\_Specialization_{i,s}$	722	1.64283	8.55934	0	187.24880
Inter-State $Lending\_Specialization_{i,s,t}$	4370	1.55694	9.71166	0	510.06570
BEA					
Sample for Intra-State Lending					
$Industrial\_Specialization_{i,s}$	646	1.04913	1.30307	0	14.20482
$Industrial\_Specialization_{i,s,t}$	3515	1.00145	0.97432	0.01243	15.08062
Sample for Inter-State Lending					
$Industrial\_Specialization_{i,s}$	722	1.06210	1.42302	0	20.06440
$Industrial\_Specialization_{i,s,t}$	4370	1.02596	1.08874	0.01056	15.08062

[39] Other items like subsidies for industries are typically negligible parts of *VA*.

[40] Using the *COMP/EMP* ratio yields similar results to those obtained with actual wages and salaries paid.

[41] Under the constant-returns-to-scale Cobb-Douglas production function, in equilibrium $r = \partial Y/\partial K = \alpha\ Y/K$ and $w = \partial Y/\partial L = (1\text{-}\alpha)\ Y/L$.

Table A2
"Stage 0″ Regressions for creating IVs as in Goetz et al. (2016). This table presents the estimates of our version of the "State 0″ regression of Goetz et al. (2016): $SHARE_{b,m,n,t} =$

$$\beta_0 + \beta_1 HQSTATE_{b,n,t} + \beta_2 Ln(DISTANCE_{m,n}) + \beta_3 HQSTATE_{b,n,t} \times Ln(DISTANCE_{m,n}) + \beta_4 Ln\left(\frac{POPULATION_{m,t}}{POPULATION_{n,t}}\right) + \beta_5 HQSTATE_{b,n,t} \times Ln\left(\frac{POPULATION_{m,t}}{POPULATION_{n,t}}\right) + \varepsilon_{b,m,n,t},$$

where, $SHARE_{b,m,n,t}$ is the percentage of deposits of MBHC *b*, headquartered in the Metropolitan Statistical Area (MSA) *m* and held in the branches of its affiliated banks in MSA *n* in year *t*. $HQSTATE_{b,n,t}$ is an indicator variable that is equal to 1 if MSA *n* is in the same state as the MBHC's headquarter MSA *m*, and 0 otherwise. *Ln* *($DISTANCE_{m,n}$)* is the natural logarithm of the miles between MBHC *b*'s headquarter located in MSA *m* and the center of MSA *n*, and captures the so-called "gravity effect" between markets. *Ln($POPULATION_{m,t}$/$POPULATION_{n,t}$)* is the natural logarithm of the ratio of the population of MBHC *b*'s headquarter MSA *m* to the population of MSA *n* in year t, and accounts for the attractiveness of the deposit market *n* with respect to deposit market *m*. Regression model is estimated using OLS and Fractional Logit. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	OLS		Fractional Logit	
Constant (β_0)	0.127	***	0.071	
	(19.77)		(0.33)	
$HQSTATE_{b,n,t}$	3.528	***	0.068	
	(32.06)		(0.27)	
Ln($DISTANCE_{m,n}$)	−0.017	***	−1.444	***
	(19.07)		(39.30)	
$HQSTATE_{b,n,t}$ ´ Ln*($DISTANCE_{m,n}$)*	−0.538	***	0.421	***
	(28.82)		(9.55)	
Ln($POPULATION_{m,t}$/$POPULATION_{n,t}$)	−0.002	***	−0.278	***
	(15.08)		(21.58)	
$HQSTATE_{b,n,t}$ ´ Ln*($POPULATION_{m,t}$/$POPULATION_{n,t}$)*	−0.143	***	−0.024	
	(25.63)		(1.37)	
Number of observations	3468,740		3468,740	
Number of clusters	5101		5101	
R^2/Pseudo R^2	0.0328		0.2662	

with direct links to our dependent variables. We further note that $w = WAGE$, $L = EMP$, and $Y/L = PROD$ (notice that we do not have a measure of TFP since we do not observe *K*). Now, assuming that we start from some equilibrium and treating banking integration as an exogenous shock, we can frame and interpret the coefficient estimates that correspond to our dependent variables given the structure that Eqs. (7) and (8) impose on them. We work with our IV estimates of our basic empirical model estimates presented in columns (1) of Table A5.

Let us first frame our basic estimates for *VA, GOS* and *COMP*. For this exercise, first we fix the capital intensity parameter α equal to 0.36 (the average for the U.S. in the period 1981–1997 as given by the Penn World Tables 8.1) and that is standard in the growth accounting literature (e.g., Barro and Sala-i-Martin, 2003). Differentiating Eq. (9) with respect to time and dividing by Y both sides, and imposing from equilibrium conditions

Table A3
Robustness checks – IV Regressions of the basic model. This table presents *IV* estimates for $\Delta\ln(VA_{i,s,t}) - \Delta\ln(VA_{j,s,t}) = \beta\ INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$. *$\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$* is the differential growth of the *Value Added (VA)* of sector *s* in state *i* and year *t relative* to the growth of the same sector *s* in state *j* and year *t*, with *i* (*j*) being the less (more) specialized state of the pair in sector *s* as of the date of effective interstate deregulation for state-pair *i-j*. In columns (1) through (3), the dependent variable is the differential growth of sector-level value-added over 2-, 3- and 5-years, respectively. Column (4) sample excludes state-pairs in which one or both of the states deregulated bank-entry without any reciprocity (i.e., National Non-Reciprocity, NNR). Column (5) sample excludes state-pairs involving a "small" state (i.e., one of the following: MT, NV, ND, SD, WY). Column (6) sample excludes state-pairs in which one had a zero-GSP growth (i.e., it excludes state-pairs if *$\Delta ln(VA_{i,s,t}) < 0$* or if *$\Delta ln(VA_{j,s,t}) < 0$*. Column (5) is estimated with the 1981–1995 sample (i.e., it excludes post-IBBEA years 1996 and 1997). *$INTEGRATION_{i,j,t}$* is based on the common banking assets belonging to MBHCs headquartered in either of the two states *i* and *j* in a given year *t*, and takes into all tertiary bank links that states *i* and *j* might have through these MBHCs' banks in other states *k, l,* etc. *$INTEGRATION_{i,j,t}$* is instrumented following Goetz et al. (2016). All regressions include state-pair-sector, state i-year, state j-year, sector s-year, and year fixed-effects. *L1* represents the 1st lag. The standard errors are clustered at the *i-j-s* level. *t*-stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	***(1)* 2-year growth**		***(2)* 3-year growth**		***(3)* 5-year growth**		***(4)* NNR States Excluded**		***(5)* Small States Excluded**		***(6)* $\Delta ln(VA_{i\ or\ j,\ s,\ t}) \leq$ 0 Observations Excluded**		***(7)* 1981–1995 Sample**	
L1.INTEGRATION	0.3749	***	0.3596	***	0.5501	***	0.2083	***	0.1723	***	0.1564	***	0.2002	***
	(5.81)		(4.10)		(3.86)		(4.35)		(4.50)		(4.21)		(5.02)	
Number of observations	155,331		103,554		68,684		164,475		239,649		268,787		258,885	
Number of clusters	17,259		17,259		17,171		9675		14,097		15,811		17,259	
Under-identification test	1028.5	***	987.3	***	901.5	***	751.3	***	929.1	***	990.8	***	923.9	***
Weak instruments test	1456.9	***	1424.0	***	1304.3	***	1067.8	***	1278.0	***	1361.6	***	1277.0	***

Table A4
Descriptive Statistics for the Components of VA. The growth of industry-level output measure Y is defined as $\Delta\ \ln(Y) = \ln(Y_t) - \ln(Y_{t-1})$. The dependent variable ($\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$) is the differential growth of output variable (Y) of sector s in state i and year t *relative* to the growth of the same sector s in state j and year t, with i (j) being the less (more) specialized state of the pair in sector s as of the date of effective interstate deregulation for state pair i-j. The industry-level output measures (Y) that are the components of VA are: *Gross Operating Surplus (GOS)* is the surplus accrued to capital from production; *Compensation of Employees (COMP)* consists of wages, salaries and social benefits paid to employees; *Employment (EMP)* is the wage and salary employment in the industry; *Productivity (PROD)* is defined as *VA/EMP*; and workers' average remuneration (*WAGE*).

	Num. of obs.	Mean	Std. Dev.	Min.	Max.
$\Delta ln(GOS_{i,s,t})$	263,431	0.07042	0.54452	−5.09068	5.24175
$\Delta ln(GOS_{j,s,t})$	270,842	0.07995	0.51989	−5.09068	5.24175
$\Delta ln(GOS_{i,s,t}) - \Delta ln(GOS_{j,s,t})$	243,650	−0.00711	0.67601	−8.28652	8.21216
$\Delta ln(COMP_{i,s,t})$	286,536	0.04893	0.11286	−1.60944	2.01490
$\Delta ln(COMP_{j,s,t})$	292,875	0.04628	0.09176	−1.60944	2.01490
$\Delta ln(COMP_{i,s,t}) - \Delta ln(COMP_{j,s,t})$	280,055	0.00235	0.13279	−2.13204	2.07944
$\Delta ln(EMP_{i,s,t})$	287,563	0.00827	0.10487	−1.52102	1.74216
$\Delta ln(EMP_{j,s,t})$	293,411	0.00353	0.08385	−1.52102	1.74216
$\Delta ln(EMP_{i,s,t}) - \Delta ln(EMP_{j,s,t})$	281,379	0.00439	0.12113	−1.87845	1.84591
$\Delta ln(PROD_{i,s,t})$	287,014	0.04754	0.14726	−1.64686	1.77876
$\Delta ln(PROD_{j,s,t})$	293,109	0.05259	0.13815	−1.38817	1.72423
$\Delta ln(PROD_{i,s,t}) - \Delta ln(PROD_{j,s,t})$	280,654	−0.00494	0.18326	−2.20637	1.92429
$\Delta ln(WAGE_{i,s,t})$	264,834	0.04403	0.04535	−0.74401	0.79271
$\Delta ln(WAGE_{j,s,t})$	275,720	0.04528	0.04241	−0.74401	0.79271
$\Delta ln(WAGE_{i,s,t}) - \Delta ln(WAGE_{j,s,t})$	245,188	−0.00119	0.05477	−0.91289	0.96690

that $GOS = \alpha\ Y$ and $COMP = (1 - \alpha)\ Y$ we obtain that $\gamma_{VA} = \alpha\ \gamma_{GOS} + (1 - \alpha)\ \gamma_{COMP}$. We find outright by estimating GDP growth differences that the less-specialized industries grow faster by 1.69% than their more specialized counterparts if integration increases from 0 to 0.01. Using estimates for the cases in which *ΔSPECIALIZATION* above the sample median from columns (1) of Table A5 for *GOS* and *COMP* and making a similar calculation we would obtain $0.36 \times 0.4160 + 0.64 \times 0.0935 = 0.2096$ which is off by 0.0427 of the *VA* estimate of 0.1669 in column (1) of Table 5. Eq. (9) suggests that the observed statistically significant increase in γ_{VA} as banking integration increases is due to both positive γ_{GOS} and γ_{COMP} differentials.

The Cobb-Douglas production framework in Equations (7) through (9) suggests that an increase in *GOS* could have four sources. *GOS* could go up due (1) an increase in capital employed K, (2) an increase in r, the demanded return on physical capital, (3) an increase in A, i.e., TFP, or (4) an increase in α, the capital intensity (or share) of the production process. Put differently, the observed increase in γ_{GOS} is due to an increase either in capital, its return, its productivity or intensity, or a combination thereof. In our context of increasing banking integration, changes in all of these are plausible. Unfortunately, the macro data at our disposal do not allow us to discern which component is more likely to be the source of higher γ_{GOS} given the increases in banking integration.[42] That said, some of the findings in the literature are supportive of at least some of these possibilities. For example, Krishnan et al. (2015) find that the TFP of small firms increases following interstate bank branching deregulations. Correa (2008) finds that the internal cash flow sensitivity of investments decreases for debt financing dependent firms following U.S. banking deregulations. Rice and Strahan (2010) use the Survey of Small Business Finance data and find that in 1993 (in a cross-sectional regression which forms a counterfactual as they focus on interstate branching deregulations) borrowing costs go down by 23 basis points for firms with higher return on assets but also by the same amount for larger small firms.[43] However, none of these studies examine the industry-specific within-bank information flows dimension as we do here.

Other consistency checks on our results that the Cobb-Douglas model imposes are the following. Since $COMP = wL$ this means that $\gamma_{COMP} = \gamma_{WAGE} + \gamma_{EMP}$. Our estimate for the difference in the growth of compensation *COMP* following integration is 0.0935, while those for wage and employment are 0.0439 and 0.0482, respectively (these estimates are from column (1) of Table A5 for *COMP, EMP*, and *WAGE*, respectively). First, this suggests that our estimates are consistent with one another as $0.0439 + 0.0482 = 0.0921$, which is close to 0.0935 by 0.0014. Second, we conclude that banking integration leads to both higher employment and wage growth in the less-specialized industries relative to the more-specialized ones. Next, as and $PROD = Y/L$ this means that $\gamma_{PROD} = \gamma_{VA} - \gamma_{EMP}$. Here our estimate of difference in growth of productivity (*PROD*) due to banking integration is 0.1235 (from Table A5) while that of *VA* and *EMP* is respectively 0.1669 (from Table 5) and 0.0482 (from Table A5). Given that $\gamma_{PROD} = \gamma_{VA} - \gamma_{EMP} = 0.1669 - 0.0482 = 0.1187$, this suggests our estimate for the growth of productivity per worker of 0.1235 is consistent with 0.1187 suggested by our simple Cobb-Douglas model (the difference being 0.0048).[44]

Finally, with Cobb-Douglas production function there is a direct link between productivity and wages (as $WAGE = (1\text{-}\alpha)\ Y/L = (1\text{-}\alpha)\ PROD$), we have $\gamma_{WAGE} = \gamma_{1-\alpha} + \gamma_{PROD}$. For the U.S., according to the Penn World Tables v.8.1 the parameter α grows from 0.346 in years 1980–1982 to 0.361 in the years 1996–1998. This implies a 0.164% fall per year in parameter $(1\text{-}\alpha)$ over the sample period. The average estimated growth of productivity, and taking the average integration as in data of 0.02, was 0.247% yearly. Then, the obtained estimates lead us to calculate $\gamma_{1-\alpha} + \gamma_{PROD} = -0.164 + 0.247 = 0.083$, which higher from our estimate of 0.0439 for γ_{WAGE}. This may be due to, for example, underestimating of the growth in the capital share parameter.

[42] Data on capital stock are publicly available either at the sectoral level for the entire U.S. or for each state but only at for all manufacturing industries combined. Even if there would be state-industry level statistics available for *K*, separating out new investments, existing capital stock and depreciation from each other would not be trivial.

[43] In the Cobb-Douglas framework this would be consistent, in equilibrium, with a lower marginal product of capital and higher capital employed by firms (holding TFP constant). More banking competition that would lower lending margins could therefore lead to an increase in investment.

[44] In additional calculations (not reported to conserve space), we used estimates of *L1.INTEGRATION* × *HIGH* from Tables 4 and A5 (with HIGH corresponding to part of the sample for which *ΔSPECIALIZATION*>industry median) and we obtained similar to the results reported here, further confirming the consistency of our estimates.

Table A5

Exploration of the underlying economic mechanism with components of VA – IV Regressions. This table presents the *IV* regression estimates for $\Delta\ln(Y_{i,s,t}) - \Delta\ln(Y_{j,s,t}) = \beta\ INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$, for different sub-samples. $\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$ is the differential growth of the output variable of sector *s* in state *i* and year *t relative* to the growth of the same sector *s* in state *j* and year *t*, with *i* (*j*) being the less (more) specialized state of the pair in sector *s* as of the date of effective interstate deregulation for the state-pair *i-j*. Output variables are defined in Table A4. $INTEGRATION_{i,j,t}$, which is based on the common banking assets, is instrumented following Goetz et al. (2016). *ΔSPECIALIZATION* is the difference specialization of sector *s* across states *i* and *j* as of date *t*. For column (2) *HIGH* (*LOW*) is an indicator variable that equals 1 if *ΔSPECIALIZATION* > (<) industry median, and 0 otherwise. In columns (3) through (7), *HIGH* (*LOW*) is an indicator variable that is equal 1 for the subsample of observations that are above (below) the median of the characteristic variable. *EFD* refers to external finance dependent sectors defined as in Rajan and Zingales (1998); *PPE/TA* is the BEA's sector-level Plant, Property, and Equipment to Total Assets ratio; *Patents* is the sector-level aggregated value of the "xi" variable in Kogan et al. (2017), which is based on the stock price reactions to individual patent announcements; *Risk (SW-Beta)* is the industry-level equally-weighted average of Scholes-William stock return beta. All regressions include state-pair-sector, state i-year, state j-year, sector s-year, and year fixed-effects. *L1* represents the 1st lag. The standard errors are clustered at the *i-j-s* level. *t*-stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

			Sample with ΔSPECIALIZATION > Median(ΔSPECIALIZATION)				
	Basic Model		***EFD***	***PPE/TA***	***Patents***	***Ind. Risk (SW-beta)***	***Durables (HIGH) vs Non-Durables (LOW)***
GROSS OPERATING SURPLUS (GOS)	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(7)***	***(6)***
L1.INTEGRATION	0.4160***						
	(3.54)						
L1.INTEGRATION × HIGH		0.6438***	1.8191***	−0.0550	0.8889***	0.5247	1.8288***
		(3.76)	(5.05)	(0.25)	(2.86)	(1.58)	(5.10)
L1.INTEGRATION × LOW		0.3089**	−0.1407	0.5958***	0.4504	0.7382***	−0.1452
		(2.45)	(0.50)	(2.63)	(1.57)	(3.26)	(0.55)
Number of observations	1493,378	143,378	71,689	71,689	71,689	71,689	71,689
Number of clusters	8434	8434	4217	4217	4217	4217	4217
Under-identification test	550.3***	344.4***	145.0***	212.4***	136.2***	146.8***	106.1***
Weak instruments test	759.6***	239.6***	89.5***	123.9***	85.3***	96.0***	71.7***
H_0: equality of coeff. estimates (Chi^2-test)		3.9**	17.4***	3.6*	1.0	0.4	18.7***
TOTAL COMPENSATION (COMP)	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(7)***	***(6)***
L1.INTEGRATION	0.0935***						
	(3.42)						
L1.INTEGRATION × HIGH		0.2065***	0.3473***	0.1271***	0.2716***	0.2486***	0.1021
		(5.09)	(4.30)	(2.79)	(3.74)	(3.39)	(1.38)
L1.INTEGRATION × LOW		0.0381	−0.0275	0.0385	−0.0667	0.0368	0.1645**
		(1.29)	(0.41)	(0.71)	(0.95)	(0.69)	(2.50)
Number of observations	238,068	238,068	119,034	119,034	119,034	119,034	119,034
Number of clusters	14,004	14,004	7002	7002	7002	7002	7002
Under-identification test	860.0***	498.7982***	204.9***	338.5***	207.5***	158.6***	210.8***
Weak instruments test	1176.3***	348.0011***	124.4***	199.0***	127.3***	104.1***	134.3***
H_0: equality of coeff. estimates (Chi^2-test)		17.0155***	11.3***	1.4	9.9***	6.5***	0.4
			Sample with ΔSPECIALIZATION > Median(ΔSPECIALIZATION)				
	Basic Model		***EFD***	***PPE/TA***	***Patents***	***Ind. Risk (SW-Beta)***	***Durables (HIGH) vs Non-Durables (LOW)***
EMPLOYMENT (EMP)	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(7)***	***(6)***
L1.INTEGRATION	0.0482**						
	(2.01)						
L1.INTEGRATION × HIGH		0.1360***	0.0924	0.0772**	0.1041*	0.1295*	0.0516
		(3.80)	(1.36)	(1.99)	(1.65)	(1.95)	(0.76)
L1.INTEGRATION × LOW		0.0050	−0.0032	0.0361	−0.0571	−0.0370	0.0215
		(0.19)	(0.05)	(0.77)	(0.90)	(0.81)	(0.38)
Number of observations	238,408	238,408	119,204	119,204	119,204	119,204	119,204
Number of clusters	14,024	14,024	7012	7012	7012	7012	7012
Under-identification test	860.8***	499.3***	205.0***	338.4***	208.3***	158.9***	211.8***
Weak instruments test	1177.4***	348.2***	124.3***	199.0***	127.7***	104.1***	134.7***
H_0: equality of coeff. estimates (Chi^2-test)		13.3***	0.9	0.4	2.9*	5.1**	0.1
PRODUCTIVITY (PROD)	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(7)***	***(6)***
L1.INTEGRATION	0.1235***						
	(4.19)						
L1.INTEGRATION × HIGH		0.1754***	0.4615***	0.0508	0.2748***	0.1560*	0.4494***
		(3.89)	(4.71)	(0.96)	(3.34)	(1.96)	(5.28)

(*continued on next page*)

Table A5 (*continued*)

					Sample with ΔSPECIALIZATION > Median(ΔSPECIALIZATION)									
	Basic Model				*EFD*		*PPE/TA*		*Patents*		*Ind. Risk (SW-beta)*		*Durables (HIGH) vs Non-Durables (LOW)*	
GROSS OPERATING SURPLUS (GOS)	***(1)***		***(2)***		***(3)***		***(4)***		***(5)***		***(7)***		***(6)***	
L1.INTEGRATION × LOW			0.0980	***	0.0121		0.1019	*	0.1016		0.2414	***	−0.0749	
			(3.20)		(0.17)		(1.89)		(1.32)		(3.90)		(0.95)	
Number of observations	238,408		238,408		119,204		119,204		119,204		119,204		119,204	
Number of clusters	14,024		14,024		7012		7012		7012		7012		7012	
Under-identification test	860.8	***	499.3	***	205.0	***	338.4	***	208.3	***	158.9	***	211.8	***
Weak instruments test	1177.4	***	348.3	***	124.3	***	199.0	***	127.7	***	104.1	***	134.7	***
H_0: equality of coeff. estimates (Chi^2-test)			3.1	*	11.9	***	0.4		2.0		0.9		18.3	***
AVERAGE WAGES (WAGE)	***(1)***		***(2)***		***(3)***		***(4)***		***(5)***		***(7)***		***(6)***	
L1.INTEGRATION	0.0439	***												
	(3.76)													
L1.INTEGRATION × HIGH			0.0632	***	0.1233	***	0.0440	*	0.1326	***	0.1376	***	0.0387	
			(3.66)		(3.36)		(1.71)		(4.00)		(4.62)		(1.37)	
L1.INTEGRATION × LOW			0.0342	***	0.0099		0.0155		−0.0225		0.0001		0.0853	***
			(2.75)		(0.39)		(0.80)		(0.82)		(0.00)		(2.61)	
Number of observations	192,372		192,372		96,186		96,186		96,186		96,186		96,186	
Number of clusters	11,316		11,316		5658		5658		5658		5658		5658	
Under-identification test	759.5	***	447.2	***	183.4	***	289.8	***	183.1	***	136.4	***	192.2	***
Weak instruments test	1043.7	***	308.2	***	110.2	***	173.0	***	109.8	***	87.8	***	117.9	***
H_0: equality of coeff. estimates (Chi^2-test)			2.8	*	5.6	**	0.7		11.0	***	14.0	***	1.0	

References

Acharya, V.V., Hasan, I., Saunders, A., 2006. Should banks be diversified? Evidence from individual bank loan portfolios. J. Bus. 79, 1355–1412.

Acharya, V.V., Imbs, J., Sturgess, J., 2011. Finance and efficiency: do bank branching regulations matter? Rev. Financ. 15, 135–172.

Aghion, P., Howitt, P., Levine, R., 2018. Financial development and innovation-led growth. Chapter 1. In: Beck, T., Levine, R. (Eds.), Handbook of Finance and Development, 3-30.

Akhavein, J.W., Frame, S.W., White, L.J., 2005. The diffusion of financial innovations: an examination of the adoption of small business credit scoring by large banking organizations. J. Bus. 78, 577–596.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econometr. 68, 29–51.

Bai, J., Carvalho, D., Phillips, G., 2018. The impact of bank credit on labor reallocation and aggregate industry productivity. J. Finance 73, 2787–2836.

Balassa, B., 1965. Trade liberalization and revealed comparative advantage. Manch. Sch. 33, 99–123.

Barro, R., Sala-i-Martin, X., 2003. Economic Growth. The MIT Press, Boston, MA.

Beck, T., and O. De Jonghe. 2013. Lending concentration, bank performance and systemic risk: exploring cross-country variation. The World Bank working paper no. 6604.

Beck, T., Levine, R., Loayza, N., 2000. Finance and the sources of growth. J. Financ. Econ. 58, 261–300.

Behn, M., R. Haselmann, A. Seru, and V. Vig. 2014. Does financial structure shape industry structure? Evidence from timing of bank liberalization. Unpublished working paper.

Bekaert, G., Harvey, C.R., Lundblad, C.T., Siegel, S., 2013. The European Union, the Euro, and equity market integration. J. Financ. Econ. 109, 583–603.

Berger, A.N., Frame, S.W., Miller, N.H., 2005. Credit scoring and the availability, price, and risk of small business credit. J. Money Credit Bank 37, 191–222.

Bernstein, S., Lerner, J., Sørensen, M., Strömberg, P., 2017. Private equity and industry performance. Manage. Sci. 63, 1198–1213.

Bertrand, M., Schoar, A., Thesmar, D., 2007. Banking deregulation and industry structure: evidence from the french banking reforms of 1985. J. Finance 62, 597–628.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econom. 87, 115–143.

Böve, R., K. Düllmann, and A. Pfingsten. 2010. Do specialization benefits outweigh concentration risks in credit portfolios of German banks? Deutsche Bundesbank Discussion Paper no. 10/2010.

Bruno, V., Hauswald, R., 2014. The real effect of foreign banks. Rev. Financ. 18, 1683–1716.

Cetorelli, N., 2004. Real effects of bank competition. J. Money Credit Bank 36, 543–558.

Cetorelli, N., Gambera, M., 2001. Banking market structure, financial dependence and growth: international evidence from industry data. J. Finance 56, 617–648.

Cetorelli, N., Strahan, P.E., 2006. Finance as a barrier to entry: bank competition and industry structure in local U.S. markets. J. Finance 61, 437–461.

Correa R. 2008. Bank integration and financial constraints: evidence from U.S. firms. Federal Reserve Board, International Finance Discussion Papers no. 925.

Damar, H.E., I. Lange, C. McKennie, and M. Moro. 2020. Banking deregulation and household consumption of durables. IWH Discussion Papers # 18/2020.

Degryse, H., S. Kokas, and R. Minetti. 2021. Banking on experience. CEPR Discussion Paper 16142.

Dumais, G., Ellison, G., Glaeser, E.L., 2002. Geographic concentration as a dynamic process. Rev. Econ. Stat. 84, 193–204.

Evanoff, D.D., Ors, E., 2008. The competitive dynamics of geographic deregulation in banking: the implications for productive efficiency. J Money Credit Bank 40, 897–928.

Financial Accounts of the United States, Federal Reserve Statistical Release: Historical Annual Tables 1985-1994. 2014. Board of Governors of the Federal Reserve System.

Fisman, R., Love, I., 2004. Financial development and intersectoral allocation: a new approach. J. Finance 59, 2785–2807.

Flannery, M.J., Watson-Hankins, K., 2013. Estimating dynamic panel models in corporate finance. J. Corp. Finance 19, 1–19.

Frame, S.W., Srinivasan, A., Woosley, L., 2001. The effect of credit scoring on small business lending. J. Money Credit Bank 33, 813–825.

Friedrich, C., Schnabel, I., Zettelmeyer, J., 2013. Financial integration and growth - why is emerging Europe different? J. Int. Econ. 89, 522–538.

Gande, A., Puri, M., Saunders, A., Walter, I., 1997. Bank underwriting of debt securities: modern evidence. Rev. Financ. Stud. 10, 1175–1202.

Goetz, M.R., and J.C. Gozzi. 2020. Financial integration and the co-movement of economic activity: evidence from U.S. states. Board of Governors of the Federal Reserve System International Finance Discussion Papers # 1305.

Goetz, M.R., Laeven, L., Levine, R., 2013. Identifying the valuation effects and agency costs of corporate diversification: evidence from the geographic diversification of U. S. banks. Rev. Financ. Stud. 26, 1787–1823.

Goetz, M.R., Laeven, L., Levine, R., 2016. Does the geographic expansion of banks reduce risk? J. Financ. Econ. 120, 346–362.

Gopinath, G., Kalemli-Özcan, S., Karabarbounis, L., Villegas-Sanchez, C., 2017. Capital allocation and productivity in South Europe. Q. J. Econ. 132, 1915–1967.

Hayden, E., Porath, D., Westernhagen, N., 2007. Does diversification improve the performance of German banks? Evidence from individual bank loan portfolios. J. Financ. Serv. Res. 32, 123–140.

Hillberry, R., Hummels, D., 2003. Intranational home bias: some explanations. Rev. Econ. Stat. 85, 1089–1092.

Jahn, N., C. Memmel, and A. Pfingsten. 2013. Banks' concentration versus diversification in the loan portfolio: new evidence from Germany. Bundesbank working paper no. 53/2013.

Jiang, L., Levine, R., Lin, C., 2016. Competition and bank opacity. Rev. Financ. Stud. 29, 1911–1942.

Jiang, L., Levine, R., Lin, C., 2019. Competition and bank liquidity creation. J. Financ. Quant. Analy. 54, 513–538.

Kalemli-Özcan, S., Sørensen, B.E., Yosha, O., 2003. Risk sharing and industrial specialization: regional and international evidence. Am. Econ. Rev. 93, 903–918.

Kalemli-Özcan, K., Papaioannou, E., Peydro, J.L., 2013. Financial regulation, financial globalization and the synchronization of economic activity. J. Finance 68, 1179–1228.
Kane, E.J., 1996. De jure interstate banking: why only now. J. Money Credit Bank. 28, 141–161.
Kerr, W.R., Nanda, R., 2009. Democratizing entry: banking deregulations, financing constraints, and entrepreneurship. J. Financ. Econ. 94, 124–149.
Kim, S., 1995. expansion of markets and the geographic distribution of economic activities: the trends in U.S. regional manufacturing structure, 1860-1987. Q. J. Econ. 110, 881–908.
Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. Q. J. Econ. 132, 665–712.
Krishnan, K., Nandy, D.K., Puri, M., 2015. Does financing spur small business productivity? Evidence from a natural experiment. Rev. Financ. Stud. 28, 1768–1809.
Kroszner, R.S., Strahan, P.E., 1999. What drives deregulation? economics and politics of the relaxation of bank branching restrictions. Q. J. Econ. 114, 1437–1467.
LaPorta, R., López-de-Silanes, F., Shleifer, A., Vishny, R., 1997. Legal determinants of external finance. J. Finance 52, 1131–1150.
LaPorta, R., López-de-Silanes, F., Shleifer, A., Vishny, R., 1998. Law and finance. J. Polit. Econ. 106, 1113–1155.
Laeven, L., Levine, R., Michalopoulos, S., 2015. Financial innovation and endogenous growth. J. Financ. Intermed. 24, 1–24.
Levine, R., 1997. Financial development and economic growth: views and agenda. J. Econ. Lit. 35, 688–726.
Levine, R., 2005. Finance and growth: theory and evidence. Chapter 12 in the Handb. Econ. Growth 1 (Part A), 865–934.
Levine, R., Loayza, N., Beck, T., 2000. Financial intermediation and growth: causality and causes. J. Monet. Econ. 46, 31–77.
Larrain, M., Stumpner, S., 2017. Capital account liberalization and aggregate productivity: the role of firm capital allocation. J. Finance 72, 1825–1858.
Levchenko, A.A., Ranciere, R., Thoenig, M., 2009. Growth and risk at the industry level: the real effects of financial liberalization. J. Dev. Econ. 89, 210–222.
Luo, M., Manconi, A., Schumacher, D., 2015. Are Investors For sale: Evidence from Financial Mergers. McGill University unpublished working paper.
Manganelli, S., Popov, A., 2015. Financial development, sectoral reallocation, and volatility: international evidence. J. Int. Econ. 96, 323–337.
Massa, M., Rehman, Z., 2008. Information flows within financial conglomerates: evidence from the banks–mutual funds relation. J. Financ. Econ. 89, 288–306.
Mian, A., Santos, J.A.C., 2018. Liquidity risk and maturity management over the credit cycle. J. Financ. Econ. 127, 264–284.
Michalski, T., Ors, E., 2012. (Interstate) banking and (interstate) trade: does real integration follow financial integration? J. Financ. Econ. 104, 89–117.
Morgan, D.P., Rime, B., Strahan, P.E., 2004. Bank integration and state business cycles. Q. J. Econ. 119, 1555–1584.
Murray, M., June 3, 1996. A newcomer to Pittsburgh finds it has a lot to prove – after acquiring Integra, National City hopes to compete with bigger banks. Wall Street J.
Paravisini, D., Rappoport, V., Schnabl, P., 2020. Specialization in bank lending: evidence from exporting firms. NBER working paper # 21800.
Rajan, R.G., Zingales, L., 1998. Financial dependence and growth. Am. Econ. Rev. 88, 559–586.
Rice, T., Strahan, P.E., 2010. Does credit competition affect small-firm finance. J. Finance 65, 861–889.
Rodano, G., Serrano-Velarde, N., Tarantino, E., 2018. Lending standards over the credit cycle. Rev. Financ. Stud. 31, 2943–2982.
Schumacher, D., 2018. Home bias abroad: domestic industries and foreign portfolio choice. Rev. Financ. Stud. 31, 1654–1706.
Stomper, A., 2006. A theory of banks' industry expertise, market power, and credit risk. Manage. Sci. 52, 1618–1633.
Tabak, B.M., Fazio, D.M., Cajueiro, D.O., 2011. The effects of loan portfolio concentration on Brazilian banks' return and risk. J. Bank. Financ. 35, 3065–3076.
Winton, A. 2000. Don't put all your eggs in one basket? Diversification and specialization in lending. Wharton Financial Institutions Center Working Paper no. 00–16.
Wolf, H.C., 2000. Intranational home bias in trade. Rev. Econ. Stat. 82, 555–563.
Wurgler, J., 2000. Financial markets and the allocation of capital. J. Financ. Econ. 58, 187–214.
Zarutskie, R., 2013. Competition, financial innovation and commercial bank loan portfolios. J. Financ. Intermed. 22, 373–396.