Financial Integration and Growth: Banks' Previous Industry Exposure Matters[*]

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This version: March 20, 2016

Abstract

We use US interstate banking deregulations to identify the effect of banks' prior to market-entry industry exposures on the output growth of states' manufacturing sectors. We examine growth of industry-level value added, gross operating surplus, total compensation, number of employees, output per employee and wages. We find that larger the discrepancy in specialization in an industry between a state-pair, higher is the impact of banking integration on the growth of that sector in the state that is less specialized. This finding is robust to the choice of estimator. Our results indicate a banking channel shaping the states' industrial landscape. (99 words)

JEL: G21, G28, F15, R12

Keywords: banking integration; industry structure; industrial specialization; economic convergence

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[*] The authors would like to thank Robert DeYoung, Cavit Pakel, and Steven Poelhekke as well as the participants at the Tinbergen Institute Amsterdam seminar, HEC Paris seminar, LabEx ECODEC Finance Workshop, 2015 Financial Engineering and Banking Society Conference in Nantes, for their valuable comments and suggestions. All remaining errors are our own. This research is partially funded by the French National Research Agency (ANR) grant number ANR-11-IDEX-0003/LabEx ECODEC/ANR-11-LABX-0047.

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1. Introduction

Over the past four decades states (countries) have become much more integrated financially, in many instances through out-of-state (foreign bank) entry. For example, banking deregulations in the US have led to the emergence of financial conglomerates that can now operate unhindered within the 50 states of the Union. A similar trend is also observed for the EU-member countries.[1] There is evidence suggesting that the effects of financial integration go beyond the simple provision of additional capital. For example, Morgan, Rime and Strahan (2004) find that there is synchronization of states' output fluctuations following integration through the banking sector. In fact, a number of papers point to a reallocation of capital across industries following financial integration (see Fisman and Love, 2004, for international evidence; Acharya, Imbs, and Sturgess, 2011, for the US; and Bekaert et al., 2013, for the EU). Yet, we know little about the micro mechanisms behind the macro-level evidence of the observed economic convergence that follows financial integration. The contribution of this paper is to explore the role of a particular channel in this reallocation process: industry-specific information collection and processing by financial institutions when providing capital to firms located in different markets that they enter. In other words, we examine whether financial integration can affect growth of various industries differently given the market-entrant financial institutions' previous exposure to the same industry.

More specifically, we test for a channel that works through commercial banks' exposure to more prevalent industries in their "home" state. Our conjecture is that financial integration with out-of-state banks that are more knowledgeable about an industry should lead to faster growth in that sector. We test this hypothesis using a series of quasi-natural experiments: staggered bank-entry deregulations at the state-pair level during 1980s and 1990s. We proceed as follows. First, we define the specialization of a manufacturing industry in a state as the ratio of that sector's share of

[1] Evidence indicates that interregional banking integration leads to more firm formation (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).

manufacturing output (i.e., value added) to its share of overall US manufacturing output.[2] Second, we presume that banks in a given state that is more specialized in an industry would naturally lend more to that sector on average (compared to banks in states in which the same sector is less specialized). Hence, prior to entering new markets banks in states that are more specialized in an industry would have, on average, more information about the functioning and prospects that sector, compared to institutions operating in states that are less specialized.[3] The information collected and processed by the banks in their (more specialized) home-state's more prominent industries would be reflected in their ability to screen and monitor loans in that sector (for ex., through specialization of lending officers or the use proprietary credit scoring systems). Third, we conjecture that when these same banks enter a new market in another state for the first time (typically through the acquisition of a local bank in their "host" state post entry deregulation), their home-state industry exposure would give these lending institutions a natural advantage in screening loans. This informational advantage would arise, for example, through the sharing (with the acquired bank) of lending officers who know of a particular industry, or proprietary credit scoring models. We justify these steps using the related evidence from the literature (see Section 2 below). Finally, using state-pair-industry-level data, we test differential growth rates of less specialized industries in a state-pair following the less specialized state's banking deregulation and financial integration with the more specialized state for a given sector.

To conduct our tests, we rely on the US data that have a number of clear advantages over cross-country studies. First, banking integration is shown to affect the real economy in the US (e.g., Morgan, Rime and Strahan, 2004, Cetorelli and Strahan, 2006, Kerr and Nanda, 2009, Rice and Strahan, 2010, Michalski and Ors, 2012). Moreover, during the years that we study, the banking sector forms roughly one-fifth to one-third of the US financial sector. So any effect that we observe is

[2] Our 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 or international trade studies. An under-specialized (over-specialized) industry would have a ratio less (higher) than one.

[3] Comparative advantage of local lenders is examined both theoretically and empirically in the literature. For example, in the Dell'Ariccia, Friedman, and Marquez (1999) model, asymmetric information between incumbent and entrant banks arises thanks to the information processing that is involved in granting prior loans to borrowers in the local market. Consistent with the hypothesis that local banks have lower information asymmetries, Bofondi and Gobbi (2006) find that Italian banks entering a new market have higher default rates than incumbents.

unlikely to be economically negligible. Second, US manufacturing firms operate in a single and fairly homogeneous economic and legal environment. As such, we do not have to worry about confounding effects (for example, differences in legal systems as documented in La Porta, et al., 1997 and 1998, among others) that cross-country studies have to deal with. Third, we concentrate our study on manufacturing industries that typically face US-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-industries.[4] Finally, and very importantly, the use of the US data allows us to control for the endogeneity of lending institutions' entry: we can instrument banking integration thanks to the staggered interstate bank-entry deregulations that took place at different points in time for different state-pairs. Our empirical set up allows us to control for existing economic conditions prior to deregulation (for example, neighborhood effects or geographic distance for a state-pair, their pre-existing industry compositions or natural endowments) as well as state- and industry-level confounding factors that vary over time.

The results are supportive of our hypothesis. First, we check whether industries in states that are classified as being less specialized in those sectors grow faster than the same industries in states that are classified as being more specialized: We observe no difference between the growth measures for industries located in states that less versus more specialized in them. This general observation holds true even when we examine quartiles of the data when we create four subsamples defined by the differences in sector-level specialization between state pairs: the growth of sectors in less versus more specialized states does not differ even when the difference in specialized is at its highest (as defined by the fourth quartile of difference in specialization). These observations are important, because we would like to rule out the possibility that the results that we find are due to the differential growth measures that we use in which the less specialized state's growth in a sector is compared to the

[4] 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 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.

growth of the same sector located in a relatively more specialized state. Then, we conduct sets of regressions, using different test variables and estimators. In these regressions we control for a very large set of confounding factors explicitly by including state-year effects, industry-year effects, state-pair-industry effects, and implicitly including state-pair-industry-years effects (since our dependent variable is differential growth of a sector between a pair of states).[5] Consistent with our hypothesis, we observe higher growth for less specialized manufacturing industries in a given state when that state's banking system gets integrated with that of another state that is more specialized in the same sectors. These findings are driven by cases in which the difference in industry specialization in a state-pair is higher, is which consistent with a re-allocation of capital.

Our coefficient estimates exhibit reasonable magnitudes. We find, for example, that for states with less specialized industries, the increase of banking integration from zero to 1.2% (the average for the estimation sample) with the more specialized states' banks leads to a differential 0.83% increase in the growth of value added over and above a comparable benchmark of the same industry in the more specialized states. We obtain similar results for the sector-level gross operating surplus (capturing the total remuneration of capital), total compensation, total number of employees, and productivity (i.e., value added by employee). These findings are stronger when we split the sample into quartiles based on the difference of state-pair's industry specializations: the coefficient estimates of interest are larger and more statistically significant in the fourth quartile (where state-pair industry specialization difference is at its highest). Moreover, these findings are robust to changes in the sample, estimation period, estimation method (OLS with IV versus Blundell-Bond with IV), and the fixed effects included in the regression.

We believe that these results are important because they provide evidence consistent with a micro-level channel for the macro-level evidence on industrial convergence provided by Kim (1995), and Dumais, Ellison and Glaeser (2002) in general, and as a result of bank branching deregulation by Acharya, Imbs, and Sturgess (2011) in particular. To the best of our knowledge, there are no papers

[5] 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).

on the sector-specific exposure of financial institutions and their industry-level impact following entry, with the exception of Bernstein et al. (2016) who provide international evidence of country-level industry growth following private equity firms' entry (we detail the differences between their paper and ours in Section 2 below).

The implications of our work go beyond academic curiosity. Our results suggest that the origins of institutions acquiring or merging with another economic region's banks can exert important influences on the industrial structure of the latter: banks, given their previous industry exposure, can play a non-trivial role in shaping industry structure of the economies that they enter. An acquirer from an economic region (state or country) that specializes in the automobile industry would have a potentially different and lasting imprint on the industrial structure (hence its future economic growth and industrial development) than an acquirer from an economic region (state or country) that specializes in the food industry.

The paper proceeds as follows. In Section 2 we review the literature important for our hypothesis. In Section 3 we detail the empirical approach and the data that we use. In Section 4 we present the main results. In Section 5 we discuss the robustness of our empirical findings and their economic relevance and consistency. Section 6 concludes.

2. Literature review

Our paper is related with different strands of the literature on financial integration and growth. First, our work is linked with the research on the growth of industries given the financial development of countries. Rajan and Zingales (1998) show that external finance dependent industries grow faster in economies with higher financial development. Wurgler (2000) finds that there is more (less) investment in growing (declining) industries in countries with more developed financial markets compared to states with a less developed financial sector. Fisman and Love (2004) find that industry growth across countries is more correlated for country-pairs with more developed financial sectors, which suggests that the financial sector, given its level of development, leads to similar shock responses across different countries. Following US interstate banking deregulations Cetorelli and Strahan (2006) find that 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. Bruno and Hauswald (2014) provide evidence that foreign bank-entry can have a positive effect on external finance dependent industries; whereas Behn et al. (2014) report that post financial liberalization industry growth depends on the interaction of domestic and foreign banks given the competitiveness of the local banking system prior to foreign bank-entry. One channel through which capital reallocation is taking place appears to be through improvements in firm productivity. Beck, Levine and Loayza (2000) find that country-level total factor productivity (TFP) growth is higher for countries that experience increases in private credit. Bertrand, Schoar, and Thesmar (2007) document that credit in France went to more productive firms following the 1985 removal of lending directives imposed on banking institutions, with deregulation leading to a change in allocations in the real economy. Using the removal of interstate *branching* deregulations of 1995, Krishnan, Nandy, and Puri (2015) find that TFP of small firms' increases following higher branching deregulation. In contrast to these papers, we show an industry's post-deregulation growth, including the growth of its productivity per worker, is affected by entrant-banks' prior exposure to that sector.

Our paper is also closely related with a smaller strand of the literature that examines the effects of financial integration across countries or states. Morgan, Rime, and Strahan (2004) find that banking integration across states helps smooth regional output fluctuations in the US while the risk of transmission of macroeconomic shocks across states increases.[6] Acharya, Imbs, and Sturgess (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 US benchmark, with the effect being driven by sectors with a larger share of young, small and external finance dependent companies. 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. Michalski and Ors (2012) show that integration of the real sector across regions follows financial integration: they find that the state-pairs that experience higher integration

[6] Goetz and Gozzi (2013), who use finer state-pair-industry-level data and interstate bank-entry deregulations for identification (as in Michalski and Ors, 2012; and Goetz, Laeven and Levine, 2013), find results that are similar to Morgan, Rime and Strahan (2004) who rely on state-level data.

following pairwise interstate banking deregulations 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 landscape, especially so after important bank-entry deregulations. Little is known so far, however, as to the micro channels through which financial integration is affecting the industrial composition of economic areas.

One exception is Bernstein et al., (2016) who study the impact of private equity firms' entry into a country on the growth of industries the former specialize in. These authors examine growth rates of productivity, employment, and capital formation at the country-industry-level with international data covering 20 sectors in 26 large economies between 1991 and 2007. They find that following PE investment in a country, the industries in which these institutions specialize enjoy higher total production, value added, total wages and employment growth. While our results complement theirs, our paper differs from Bernstein et al. (2016) in many dimensions. First, we use the US 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 our case financial integration between pairs of states could not increase before interstate banking deregulations became effective. This allows us to use a clear identification scheme that varies over time and state-pairs. In contrast, pinning down identification is much harder in an international setting as it is very difficult, if not impossible, to find exogenous changes that would generate strong instrumental variables. Without exogenous deregulatory events similar to ours, it is also more difficult in cross-country studies to account for the possible effects of other developments in the financial sector.[7] Second, during the period covered in our study the commercial banks' role in the US remains very important: 21.1% to 34.5% of the financial sector total assets in 1994 and 1985, respectively (Financial Accounts of the United States, 2014). Other segments of the financial industry were less influential during these years (and remain so in international settings even today). Importantly, in the US 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.

[7] For example, Behn et al. (2014) use international data and find evidence of industry-level growth after major financial deregulations, which are typically followed by foreign bank entry. However, they do not examine whether foreign banks' pre-entry industry exposure plays a role in that sector's growth in the host country.

As such, we can clearly establish a causality running from banking integration to industry growth. Third, our US setting allows us to conduct counterfactual exercises by examining the growth of less specialized sectors when banking integration takes place with states that are also less specialized in the same industries. Such exercises allow us to rule out the possibility that our results are merely driven by statistical artifacts. Finally, we conduct a series of additional regressions and observe that our empirical results are robust. Moreover, a simple calculation exercise based on a Cobb-Douglas production model allows us to check the consistency of our various estimates with respect to each other. In the next section we review our approach for identifying the impact of banking integration on industry growth, define the empirical specification that we use, and provide information on the data and their sources.

3. Identification, empirical specifications, and the data

3.1. Identification

Before explaining the empirical strategy that we follow to test our conjecture, first we clarify the economic channels that are behind our hypothesis. We conjecture that less specialized industries in a state would grow faster if their state experiences banking integration with other states in which the same sector is more specialized.

Our conjecture requires that industry-specific information (for example, in the form of proprietary credit scoring models, or transferring loan officers) be shared among banks belonging to a multi-bank holding company (MBHC):[8] i.e., that the sector-specific information flows from a member bank located in a state that is more specialized in a particular industry, to another affiliated bank operating in a state that is less specialized in the same industry. MBHCs play a central role in our story because following interstate banking deregulations, which we use to identify banking integration's effect, bank-entry took place through the acquisition of deregulating states' banks by out-of-state banking conglomerates.[9] In this setting, a natural way for information to flow within the

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[8] MBHCs were a common form of banking conglomerate in the US during the 1980s and 1990s.

[9] Banks were able to open new branches across state lines (if the host state allowed it) after the adoption of the 1994 Interstate Bank Branching and Efficiency Act (IBBEA, also known as the Riegle-Neal Act), which become effective in 1995. As the data available to us do not extend beyond 1997, we cannot exploit this

expanding MBHC would be the sharing of proprietary credit scoring systems of previously separate banking entities.[10] Such information flows between banks of the same financial conglomerate are to be expected given evidence in the literature 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. Newer evidence on mutual funds by Luo, Manconi and Schumacher (2014) suggests that target (acquirer) funds start investing in sectors that the acquiring (targeted) fund used to invest in prior to the acquisition. More pertinently for our conjecture, Schumacher (2015) 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).

There is also another strand of the literature (Winton, 2000, and Stomper, 2006) that makes theoretical arguments for the sector-level specialization of banks in their lending.[11] However, the related empirical evidence to date is mixed.[12] That said, for our conjecture to go through we do not

legislative change, which, for example, Krishnan, Nandy, and Puri (2015) use to examine the effect of more bank finance on firms' TFP.

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

[11] 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.

[12] Using Italian data Acharya, Iftekhar, 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, Iftehar 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. In contrast, Beck and De

need banks coming from states that are more specialized in certain industries to be 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. In our story, the newly acquired bank would improve its lending with better screening through the additional sector-specific information provided by the acquiring-MBHC that operates in states that are overspecialized in the same sector. The information channel is especially pertinent for states that are less specialized in an industry, which are the focus of our paper. Our set-up allows us to account for the size of the difference in industry-specific specialization "gap" between any two state-pairs. We find that when the difference in specialization of states in a given industry is small banking integration has no effect on differential industry growth. The effects that we observe are driven by cases in which a state-pair has a large difference in its specialization in a given industry. Next, we provide a discussion of the problem of endogeneity that we face in conducting our analysis.

Ideally, a direct test of our hypothesis would involve data on the sector composition of US banks' loan portfolios before and during the integration process: post-acquisition by MBHCs from states that are more specialized in a sector, we should observe an increase in the segment-level lending by the (acquired) banks in the state that is less specialized in the same industry.[13] Unfortunately, such industry-level decomposition of bank lending is not available in the financial statements (the, so-called, Call Reports) that all the US commercial banks have to file with the federal regulators. Instead, we rely on state-industry-year level data and regress the annual growth rates of less specialized industries on, among other variables, a test variable that captures state-and-industry-specific bank-integration with more specialized states (more detail is provided in Section 3.2). However, such regressions would be biased and inconsistent if bank-integration would be endogenous to industry structure in general and industry growth potential in particular.

Jonghe (2013) examine an international sample of large banks and find that sector-level specialization generates higher volatility and lower returns.

[13] We know of no evidence to date on post bank-acquisition portfolio convergence for commercial and industrial loans at the industry level. That said, there is limited anecdotal (e.g., Wall Street Journal, 1996) and empirical (e.g., Zarutskie, 2013) evidence of portfolio harmonization across loan categories for banks (i.e., business loans, real-estate loans, personal loans, etc.).

From one point of view, endogeneity is not likely to be a major concern: 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 improbable that the industries in which a state is less specialized (i.e., smaller), and on which we focus, would be the driving lobbying force for interstate bank-entry deregulation at the state legislature. Nevertheless, even if the deregulation process is not likely to be endogenous to the growth of less specialized industry segments, some banks' entry decisions might be endogenous: at least some MBHCs' entry may have been driven by opportunities in lending growth. If so, our banking integration might be endogenous to the growth of industry segments.

This is where the staggered series of interstate banking deregulations provide us with a powerful identification tool at the state-industry-level through the use of instrumental variables approach similar to Morgan, Rime and Strahan (2004), Michalski and Ors (2012), and Goetz, Laeven, and Levine (2013). Because both our bank integration variable and the IVs vary at the state-industry-year-level, we can identify the impact of integration of a state's banking system with those located in states that are more specialized in an industry.

Finally, interstate banking deregulations also allow us to come up with the proper counterfactuals to rule out the possibility that our regressions are merely picking up spurious correlations. If the information channel we have in mind would hold true, then we should observe *no* effect when a state that is less specialized in certain industry segments would find its banking system integrated with banks of other states that are also less specialized in the same industry. This is exactly what we find: if a state ends up with more banking links with another state that is similarly specialized in a given industry, that sector does not experience higher growth. Put differently, such integration provides no additional benefits in terms of information flows, loan screening and monitoring for the concerned industry.

3.2. Empirical specifications

In this section we introduce the regression specifications and variables that we use and detail the empirical challenges that we face. We first calculate the annual state-level specialization for each of the 19 two-digit SIC manufacturing industries.[14] As mentioned earlier, specialization is defined as the ratio of a sector's share of state's manufacturing output (i.e., value added) to the same sector's share of overall US manufacturing output.

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

$$\Delta \ln\left(Y_{i,s,t}\right) - \Delta \ln\left(Y_{j,s,t}\right) = \beta_1\, L1.DEREGULATED_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t} \qquad (1)$$

where, $\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$ 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*;[15] $DEREGULATED_{i,j,t}$ is an in indicator variable that is equal to 1 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 0 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. The six output variables (*Y*) used in the analysis are defined in Section 3.3 below. It should be noted that this is a very demanding specification. The annual differencing of industry growth rates at the state-pair level takes out the effects of any shock that affects a particular industry at the state-pair level in a given year. Furthermore, $\delta_{i,j,s}$ fixed-effect soaks 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 such, the initial tendency of small sectors (that would

[14] As explained in Section 3.3 below, 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).

[15] $\Delta ln(Y_{i,s,t})$ 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.

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-effect accounts for any observable or unobservable *pre-conditions* (such as sector-specific endowments, or lack thereof) that might have an impact on sector specific growth. 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, the effects of state-wide legislation, for example about minimum wages, etc.) Industry-year fixed-effects ($\gamma_{s,t}$) account for time-varying developments in sector *s* at the US-level that could exacerbate the growth of more or less specialized industries (our differenced specification implicitly takes care of industry-year growth that is common for all states). We also have year fixed-effects, δ_t, to account for the growth of the US economy (of course, one of the many fixed-effects that each of $\delta_{i,t}$, $\delta_{j,t}$ and $\delta_{s,t}$ involve is dropped to avoid multicollinearity with $\delta_{j,t}$).

In equation (1) the dependent variable ($\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$) is at the state-pair-industry-time level whereas the test variable ($DEREGULATED_{i,j,t}$) varies at the state-pair level. This is likely to render identification difficult, as our hypothesis suggests that entry by banks from states that are more specialized in sector *s* into states that are less specialized in the same industry should lead to higher growth of *s* in less specialized states. One way to improve identification is to take into account the discrepancy in specialization in a given industry. The larger the difference in specialization in *s* in a deregulating 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 and state *j* is over-specialized. Small differences in sector-specific specialization of state-pair *i-j* would amount to comparing growths of sectors in which both states are similar in terms of specialization. That is, small differences in specialization would be akin 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 specific informational advantages to banks of state *j* entering state *i*.

To functionalize this improvement in identification, we define $\Delta SPECIALIZATION_{i,j,s} = |SPECIALIZATION_{i,s} - SPECIALIZATION_{j,s}|$ where specializations are defined as of the year of effective banking deregulation of state-pair *i-j*. There are different ways to incorporate this difference (or lack thereof) in specialization in a state-pair into our tests. One possibility is to run Equation (1) after having classified all observations pertaining to state-pairs per industry by the difference in specialization in that sector (as of the interstate banking deregulation) and run separate regressions. We do so after classifying all observations in state-pair in a given industry s into quartiles of $\Delta SPECIALIZATION_{i,j,s}$. Another possibility is to run a modified version of Equation (1) in which we interact $DEREGULATED_{i,j,t}$ with $\Delta SPECIALIZATION_{i,j,s}$:

$$\Delta \ln\left(Y_{i,s,t}\right) - \Delta \ln\left(Y_{j,s,t}\right) = \beta_1 L1.DEREGULATED_{i,j,t} + \beta_2 L1.DEREGULATED_{i,j,t} \times \Delta SPECIALIZATION_{i,j,s}$$
$$+\delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t} \qquad (2)$$

where all of the variables are as defined above.[16]

One weakness of equations (1) and (2) 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:

$$\Delta \ln\left(Y_{i,s,t}\right) - \Delta \ln\left(Y_{j,s,t}\right) = \beta_1\, L1.INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t} \qquad (3)$$

where, $INTEGRATION_{i,j,t}$ 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 (banking assets of either state's MBHCs that are located in other states are not taken into account in this calculation). As in the case of Equation (2), to improve identification, we also interact $INTEGRATION_{i,j,t}$ with $\Delta SPECIALIZATION_{i,j,s}$:

$$\Delta \ln\left(Y_{i,s,t}\right) - \Delta \ln\left(Y_{j,s,t}\right) = \beta_1\, L1.INTEGRATION_{i,j,t}$$
$$+\beta_2\, L1.INTEGRATION_{i,j,t} \times \Delta SPECIALIZATION_{i,j,s}$$

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

$$+\delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t} \qquad (4)$$

where, all of the variables are defined as above.

However, equations above could still suffer from a number of problems. First, as explained above in Section 3.1, banking integration can be endogenous to manufacturing sectors' growth differentials. To deal with this potential problem, we run versions of equations (3) and (4) using Instrumental Variables (IV) estimation. As an instrument, we use the sum of average number of years since the effective deregulation (*YEARS_SINCE*) between each state-pair that we lag by one year in actual estimation.[17] This instrument has the benefit of capturing succinctly the dynamics of different types of deregulatory processes for interstate bank entry that were put in place in the US between 1977 and 1995. In some instances, state *i* and *j* permitted entry only based on reciprocity, in which case the effective date of opening is that of the state that allows (reciprocal entry) the latest. For example, if state *i* does (reciprocal) entry deregulation in year 1986, and state *j* does the same but only on December 31st, 1990, *YEARS_SINCE* will be equal to 0 in all years prior to 1991 and 1 for all years after 1990. In this case, the average years since deregulation will be equal to 1 for 1991, 2 for 1992, 3 for 1993 and so on: this is because the number of years since effective deregulation goes up by the same increment of 1 by each for both states *i* and *j*. In other instances, some states decided to open up their banking markets in a non-reciprocal way (i.e., irrespective of the regulatory stance of the counterparty state). Suppose that state *i* non-reciprocally deregulated in 1986 but *j* allows interstate bank entry in a reciprocal way as of 1990. In this case the average number of years since deregulation would be equal to 0 prior to 1987, it will be equal to 0.5 for 1987, 1 for 1988, 1.5 for 1989, 2 for 1990 (the year of reciprocal opening of state *j*), and be equal to 3 in 1991, 4 in 1992, and so on.

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

[17] In the estimation we use *L1.YEARS_SINCE* as an IV, since the instrumented variables are themselves lagged one year to avoid simultaneity. As an alternative IV, we also use the square root of the years since effective deregulation (but without taking the average, which could make a difference in case of non-reciprocal deregulations, as we explain in the text). Our IV-regression results are not affected by the choice of the instrument.

specialized) are likely to 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.[18] 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 assure ourselves of the robustness of our results. The numbers of lags that are introduced (say, in *Within* regressions), which depend on the dependent variable, are defined by the tests conducted during Arellano-Bond regressions that we run (see the next paragraph).

The final issue that we need to take into consideration in this dynamic panel setting is the fact that we would also like to control for the unobservables with industry-time and state-time fixed effects. The problems cited in the previous paragraph would be exacerbated by the fact that including a large number of fixed effects in dynamic panel models can lead to biased and inconsistent estimators, especially for "small T, large N" panels (Nickell, 1981). Judson and Owen (1999) state

[18] 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.

that the bias is inversely related to panel length T, since the effect of idiosyncratic shocks will decay overtime. Given that our data panel has moderately few time periods (T=17) but large N (with a maximum of 21,342 observations in each year for 19 manufacturing industries in (48×47)/2 = 1,128 state-pairs) our regressions are potentially prone to "dynamic panel bias". Under such conditions, the Arellano-Bond (AB) estimator (following Arellano and Bover, 1995, and Blundell and Bond, 1998), which relies on the generalized method of moments (GMM), provides a solution for the efficient estimation of dynamic panels.[19] This estimator corrects for the endogeneity of the lagged dependent variable (which is introduced to control for its persistence or mean-reversion) and provides consistent parameter estimates even in the presence of endogenous right-hand-side variables (in our case, the bank-integration variable). It also allows for fixed effects, heteroskedasticity and autoregressive (AR) error terms. Since our dynamic panel exhibits all of these characteristics in some of our regressions we use the Blundell and Bond (1998) system-GMM (BB) estimator for dynamic panel data. We do this because system version of the AB estimator involves first-differencing of the regression equation of interest and building a system of two equations -- the original equation and the transformed one -- an approach that provides more suitable instruments (e.g., Roodman, 2009) for our lagged dependent (difference of growth) variables.[20, 21, 22]

3.3. The Data

To construct our database we rely on two separate sources. First, we use annual Bureau of Economic Analysis (BEA) estimates of state-and-industry output variables. The benefit of the BEA

[19] Due to the problems associated with AB-estimator, we rely on a set of estimators to check the robustness of our results to estimator choice.
[20] For a similar application of system-GMM proposed by Blundell and Bond (1998) to country-level growth rates see Beck, Levine and Loayza (2000) as well as Levine, Loayza and Beck (2000), and to (external finance dependent) industries' growth rates see Bruno and Hauswald (2014).
[21] 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 for practical applications a system-GMM over alternative estimators.
[22] When using the system-AB estimator, 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 (AR) patterns. To accommodate such differences we make use of the Arellano-Bond 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.

data is that they help us assess the overall economic impact of banking integration on 19 industrial segments (as opposed to the overall state-level output growth).[23] The downside is that state-industry-level value added, which is equal to state-industry level Gross State Product (GSP), is a BEA estimate based on industry-level US Census Bureau data.[24] Nevertheless, we use BEA's manufacturing segment-level aggregate data, as they are the only publicly available state-industry-year level data that can be obtained. Second, we use BHC and commercial bank financial statements to calculate the banking integration variable across state-pairs. These data come from the financial statements (the so-called Call Reports and Y-9 forms) that all US banks and BHCs have to file with their federal regulators.[25]

We use 1972-1997 BEA data to estimate our regression equations over 1981-1997 (the difference is due to the lags that we introduce in some regressions, especially those estimated with the system-AB estimator). We start in 1981 for two reasons. First, we do not have BHC structure (i.e., membership) data prior to 1981.[26] 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. We take into account the IBBEA, which took effect in September of 1995 and 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 opening new branches (if the states allowed such branching entry). It should be noted that we cannot go beyond 1997 because of changes in the industry classification standards.[27]

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[23] An alternative source of data, available from the Annual Survey of Manufacturing (ASM), and containing the more data, 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 it 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 crucially when the estimation requires dynamic panel techniques with lagged variables as instruments.

[24] GSP is the state-level equivalent of the country-level Gross Domestic Product (GDP).

[25] These are the Federal Reserve System, the Office of the Comptroller of the Currency, and the Federal Deposit Insurance Corporation.

[26] 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.

[27] In 1997 the US 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

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 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. In the fourth column of Table 1 we indicate the nine industries that we classify as more external finance dependent as they are the median of the measure proposed by Rajan and Zingales (1998).[28] In column five (six) 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 31.1 (16.7) states on average. There is variation on this dimension across industries: an industry can be under-specialized (over-specialized) in 24 to 40 (8 to 24) states.

Table 2 provides the summary statistics for the variables that we use. The average of $SPECIALIZATION_{i,s}$ is equal to 0.59 with a standard deviation of roughly 0.35 while that of – $SPECIALIZATION_{j,s}$ where is equal to 1.19 with a standard deviation of roughly 0.58. The average of $\Delta SPECIALIZATION$ is equal to 0.60 and has a standard deviation of 0.5: at the state-pair-industry level there is a lot of variation in industry specialization, which is important for us to be able to conduct the tests of our hypotheses. We don't want our empirical results to be driven by accentuated growth patterns of highly 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*.[29] To have a proper panel

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.

[28] 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.

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

without missing observations, we keep only state-pair-industry observations for which we have no missing values over 1981-1997.[30]

In Table 2 we provide two sets of statistics for output measures. First, we provide state-industry-level output growth for each state in a pair *i-j*: we do this to check whether output growth measures differ systematically across pairs *i-j*. Second, we provide statistics on our dependent variables. We have six dependent variables as measures of state-industry-level growth. Value added (*VA*) is equivalent to state-industry-level GSP. Gross Operating Surplus (*GOS*) is the return to the capital employed in the industry at the state level. Compensation of employees (*COMP*) is the total of disbursements to industry's employees (including wages plus retirement and similar contributions made by the employers). It should be noted that *GOS* and *COMP* are the two main components of *VA*.[31] The number of employees (*EMP*) at the state-industry level includes both full- and part-time employees (without a full-time equivalent adjustment unfortunately). Productivity (*PROD*) is measured as value added per employee at the state-industry level. Similarly, wages (*WAGE*) is gross compensation per employee at the state-industry level. In Section 5.2, we provide a simple Cobb-Douglas production model and show how these six variables are linked with each other.

In Table 2, we observe little difference in annual output growths at the state-industry level. For example, the average for $\Delta ln(VA_{i,s,t})$ is equal to 0.056 (i.e., 5.6%) and so is the average for $\Delta ln(VA_{j,s,t})$. For other variables, there are slight differences in the growth rates for *GOS* (with averages of 7.0% and 7.6% for *i* and *j*, respectively), *COMP* (averages of 4.95% and 4.66%), EMP (0.8% and 0.35%), PROD (4.7% and 5.3%), and WAGE (4.1% and 4.3%). The somewhat sizeable standard deviations observed in Table 2 for some of these growth rates are due to the fact that we are dealing with relatively small industries (in which their state is less specialized) whose growth can change by large values year-to-year if (relatively) few establishments are launched or closed. Unsurprisingly, the averages of our dependent variables, the differential output growths ($\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$) are close to zero: the average for VA is equal to 0.0003, for GOS –0.0064, for COMP 0.0029, for EMP 0.0049, for PROD –0.0058, and for WAGE –0.0020. However, we only cannot reject the hypothesis that the

[30] The gaps in the data are due to zeros or values that are unreported by the BEA for various reasons.
[31] Other items like subsidies for industries are typically negligible parts of VA.

difference in VA growth is not different from zero at the 10% level. This means that although in all the less-specialized industries grew roughly at the same pace as the more-specialized ones (as defined by the ordering in our pairs) their increases in employment that were driving the compensation component of the VA were faster than those of more-specialized industries. The opposite was true for the GOS. Next, we discuss our results, which are presented in Tables 3 through 7.

4. Main results

In Table 3, we provide the estimates of Equation (1). In Panel A, we present the coefficient estimates for *L1.DEREGULATED* of Equation (1) using the Within estimator with each output measure in a given column representing a different regression. For *VA* the estimate of β_1 is equal to 0.0118, which is statistically significant at the 1%-level. This finding suggests that, after interstate bank-entry deregulation, less-specialized industries in states denoted *i* grew 1.18% faster than relatively more specialized industries in states denoted *j*, on average. Similar results are obtained across the columns for all of the output variables, except one. For *GOS* the estimate of β_1 is equal to 0.0262, for *COMP* to 0.0062, for *EMP* to 0.0052 and for *PROD* to 0.0059, all of which are statistically significant at the 1%-level. Only *WAGE* does not appear indicate differential growth after state-pair bank-entry deregulation when we examine states that are less specialized in the sector versus those that are more specialized: the coefficient estimate is equal to 0.0007 and not statistically significant. These results suggest that banking deregulation (that potentially leads to bank-entry) affects the growth of sectors in states that are less specialized compared to states that are more specialized: after deregulation gross operating surplus increases by 2.62%, aggregate sector-level compensation by 0.62%, employment by 0.52% and productivity (as measured by value added by employee) by 0.59%.

We first would like to make sure that these results are not an artifact of the dynamic panel that might be present in our data series. To do so, in Panel B of Table 2, we use *Within* regressions to estimate versions of Equation (1) that include lags of the dependent variable (difference in growth across states for the same sector), with the lag structure being determined by tests conducted in Arellano-Bond regressions (which are not reported to conserve space, but are available upon request).

For the coefficient of interest, the results of Panel B are very similar to those of Panel A: For *VA* the estimate of β_1 is equal to 0.0123, for *GOS* to 0.0265, for *COMP* to 0.0059, for *EMP* to 0.0049 and for *PROD* to 0.0064, all of which are statistically significant at the 1%-level; whereas the estimate for *WAGE* is equal to 0.0008 and not statistically significant.

These results suggest that interstate bank-entry deregulation has a differential impact. However, they do not clarify whether the observed effect is due to less specialized (most likely smaller) industries having access to more finance or whether the said deregulations lead to redistribution of lending given the informational advantages some banks coming from states that are more specialized in the industry might have. We address these questions in a number of steps.

First, we examine whether the observed effect of interstate bank-entry deregulation (which could potentially lead to banking integration) increases as the difference in sector-specific specialization between two states is larger. This can be addressed in two ways: estimating Equation (1) for different subsamples given the quartiles of *ΔSPECIALIZATION* or by interacting this variable with the deregulation indicator variable. If the story is one about an increase in the provision of loans (without a sector-specific role for banks' prior exposure to the industry), then in either approach we should observe that deregulation should lead to an increase in growth, irrespective of the discrepancy in sector-related specialization between state-pairs that deregulate bank entry.

In Panel A of Table 4, we present estimates for the coefficient of *L1.DEREGULATED* in Equation (1), which are estimated without any lags, for different samples of the data by quartiles of *ΔSPECIALIZATION*. For *VA* the estimate of β_1 is equal to 0.0022 (not statistically significant) in the first quartile of *ΔSPECIALIZATION*, to 0.0067 (and statistically significant at 10%-level) in the second quartile, to 0.0204 (which is statistically significant at the 1%-level) in the third quartile, and to 0.0108 (statistically significant at the 15-level) in the fourth quartile. Similar patterns for the estimate of β_1 are also observed for productivity: for PROD β_1-estimates are 0.0006, 0.0063, 0.0083, 0.0078 across quartiles 1 through 4, respectively, with the latter three estimates being statistically significant at the conventional levels. For other measures of output, the pattern is still there, even if less clearly. For example, for GOS β_1-estimates are 0.0185, 0.0373, 0.0316, 0.0192 for quarters 1 through 4, respectively, but only the second and third quarter results are statistically significant (at 1%-level).

To further examine the issue, we estimate Equation (2), without any lags, in which *L1.DEREGULATED* is interacted with *ΔSPECIALIZATION* and present the results in Panel B of Table 4. The coefficient β_2 estimate for the *L1.DEREGULATED×ΔSPECIALIZATION* interaction is positive for *VA* (0.0067), *COMP* (0.0046), and *EMP* (0.0053) and statistically significant at the 1%-level. The β_2 estimates for *GOS*, *PROD* and *WAGE* are small and not statistically significant.

These results provide first evidence for our hypothesis that banks' previous exposure to a sector matters when the same institutions enter a new market. Value added is impacted differentially for less-specialized industries; and it is driven by increases in employee compensation which in turn is affected by an increase in employment. But this does not give the full picture, however. *DEREGULATED* accounts for state-pairs' bank-entry liberalization, but does not account for *actual* bank entry, something we take into account in the next set of tables.

In Panel A of Table 5, we present β_1-estimates for *L1.INTEGRATION* when Equation (3) is estimated using IV approach (but without adding any lags of the dependent variable). The coefficient estimate for *VA* is equal to 0.6944, which is statistically significant. This suggests that one standard deviation increase (0.0112) in banking integration across state-pairs leads to a 0.78% (=0.6944×0.0112) differential growth for industries across the same state-pairs. Similarly, one standard deviation increase in banking integration leads to a 0.42% (=0.3554×0.0117) differential growth for *COMP*, 0.22% (=0.1878×0.0117) differential growth for *EMP*, 0.36% (=0.3117×0.0117) differential growth for *PROD*, and 0.18% (=0.1878×0.0117) differential growth for *WAGE*. The coefficient estimate for *GOS* is equal to 0.4190 but not statistically significant.

The results are stronger in Panel B of Table 5 when we estimate Equation (3) with the proper number of lags for each growth measure so as to properly take into account the autocorrelation in the dynamic panels that we work with. The coefficient estimate for the interaction terms is statistically significant either at 5% or 1%-level for all of our output measures: β_1-estimate is equal to 0.9391 for *VA*, 0.7600 for *GOS*, 0.3779 for *COMP*, 0.1475 for *EMP*, 0.4340 for *PROD*, and 0.1802 for *WAGE*. For one standard deviation increase in bank integration, these results suggest differential growth rates of 1.05% for value added, 0.93% for gross operating surplus, 0.44% for compensation, 0.17% for employment, 0.50% for productivity, and 0.21% for wages.

Of course, these results do not necessarily corroborate our hypothesis that banks' prior exposure to an industry matters for that industry's growth when the sector-exposed banks enter a new market. For a better test of our hypothesis, we re-estimate our IV-regressions using different quartiles of the data according to differences in specialization. In Panel A of Table 7, there is a clear monotonic increase in the coefficient estimate of *L1.INTEGRATION* with increasing quartiles of *ΔSPECIALIZATION*. For example, for value added β_1-estimates are 0.1299 (not statistically significant) for the first quartile, 0.5315 (and statistically significant at the 1%-level) for the second quartile, 1.1835 (and statistically significant at the 1%-level) for the third quartile, and 1.6907 (and statistically significant at the 1%-level) for the fourth quartile. A similar monotonic increase in β_1-estimates is now observable for all of the output variables. For example, going from the first through quartile for compensation the β_1-estimates are equal to -0.0474, 0.2853, 0.7179, 1.0894, and all of which are statistically significant at the conventional levels, except the very first estimate. These findings, which also hold for other output measures, indicate that the higher the difference in state *i*'s specialization in sector *s* compared to state *j*, the higher the impact of *actual* banking integration. This evidence is consistent with our hypothesis that banks' prior industry exposure matters.[32]

In Panel B of Table 7 we present the estimates of Equation (4), in which *L1.INTEGRATION* is interacted with *ΔSPECIALIZATION*. The β_2-estimates for the interaction are positive and always statistically significant at the conventional levels (10%-level for *WAGE*). These results are supportive of the findings we had in Panel A of the same table.

5. Checks on the consistence and robustness of the results

To check the robustness of our results we conduct two additional exercises. First, in Section 5.1, we repeat our estimates of Equation (3) after separating the data at our disposal into two

[32] More direct tests would involve repeating the exercise in Table 7 (or Table 5) after limiting the sample to cases in which state *i* is under-specialized in sector *s* (i.e., $SPECIALIZATION_{i,s} < 1$) while state *j* is over-specialized in the same sector (i.e., $SPECIALIZATION_{j,s} > 1$). These are being prepared for the next version of the paper.

subsamples based on industries' external finance dependence (as in Rajan and Zingales, 1998). In Section 5.2. we further check on the internal consistency of our estimates using a simple calculation exercise.

5.1. Checks on the robustness of the empirical estimates

If our conjecture holds true, the effects that we observe in Section 4 should be more pronounced for the external finance dependent (EFD) industries. Given Rajan and Zingales (1998) findings, it is natural to think that industries with higher EFD might benefit more from the industry-specific information flow induced by the banking integration across state borders. Put differently, if our hypothesis is true, we should observe stronger results for high-EFD manufacturing industries and weaker results for low-EFD industries. To test for these possibilities, we use the industry-level measure of external finance needs developed in Rajan and Zingales (1998) and divide our sample into two mutually exclusive subsets. The first subset contains nine industries that exhibit higher EFD in our sample, while the latter contains ten industries that have relatively low EFD in our dataset.

The results for Equation (3) with IV-estimation are presented in Table 7, in which Panel A presents the low-EFD subsample results and Panel B presents the high-EFD subsample results.[33] The coefficient estimate for the differential growth of value added for the low-EFD sample is equal to 0.4211 (statistically significant at the 1%-level), whereas the comparable estimate for the high-EFD subsample is equal to 1.0031 (statistically significant at the 1%-level). Results *PROD* and *WAGE* exhibit a similar pattern. For the low-EFD sample the coefficient estimate for *PROD* is equal to 0.1773 (statistically significant at the 10%-level) whereas for the high-EFD the coefficient has an estimate of 0.4894 (statistically significant at the 1%-level). For *WAGE* the low-EFD sample coefficient estimate is equal to 0.1124 (statistically significant at the 5%-level) whereas for the high-EFD the coefficient has an estimate of 0.2088 (statistically significant at the 1%-level). Similar results also hold for *GOS*, *COMP* and *EMP*, with the exception that low-EFD coefficient estimates are not statistically significant. For *GOS* the Equation (3) β_1 coefficient estimate is equal to -0.1326

[33] We also replicated Tables 4 and 6 for low- and high-EFD subsamples and observed a pattern similar to the one described in this paragraph.

(statistically insignificant) for the low-EFD, 0.9571 (statistically significant at 5%-level). For *COMP* the Equation (3) β_1 coefficient estimate is equal to 0.0391 (statistically insignificant) for the low-EFD, 0.7347 (statistically significant at 1%-level). Similarly, for *EMP* the Equation (3) β_1 coefficient estimate is equal to -0.0733 (statistically insignificant) for the low-EFD, but equal to 0.4897 (statistically significant at 1%-level). The fact that high-EFD results are always positive, statistically significant, and roughly twice the size of the low-EFD estimates (when the latter are statistically significant) is further evidence that is consistent with our conjecture.

5.2. Consistence check through a simple calibration exercise

Finally, to frame the findings of Sections 4 and 5.1, we conduct a simple, partial equilibrium, calculation exercise relying on a representative production function. The model is kept purposefully simple. 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 our coefficient estimates with respect to each other. 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:

$$Y = A(K)^{\alpha}(L)^{1-\alpha} \qquad (2)$$

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 equilibrium conditions that marginal products of capital and labor are going to be equal with the return on capital (r) and wages (w), respectively, we can rewrite Eq. (2) as: [34]

$$Y = rK + wL \qquad (3)$$

Substituting value added for *Y*, gross operating surplus (i.e., remuneration of capital) for *rK*, and compensation of labor for *wL*, Eq. (3) becomes:

$$\mathrm{VA} = \mathrm{GOS} + \mathrm{COMP} \qquad (4)$$

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 don't observe *K*). Now, assuming that

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

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 equations (3) and (4) impose on them. We work with our preferred estimates of the effects of integration on our variables of interest for the fourth quartile of *ΔSPECIALIZATION* shown in Table 6.

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. (4) with respect to time and dividing by Y both sides, and imposing from equilibrium conditions 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. Running the estimations separately for *GOS* and *COMP* and making a similar calculation we would obtain 0.36×2.5553 + 0.64×1.0894 = 1.617 which is close to the GDP estimate of 1.69%. Eq. (4) 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 between less- and more- specialized industries.

The Cobb-Douglas production framework in equations (2) through (4) suggests that an increase in *GOS* could have four sources. *GOS* could go up due (i) an increase in capital employed K, (ii) an increase in r, the demanded return on physical capital, (iii) an increase in A, i.e., TFP, or (iv) 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.[35] That said,

[35] Data on capital stock are publicly available either at the sectoral level for the entire US or for each state but only at for all manufacturing industries combined. Even if there would be state-industry level statistics available

some of the findings in the literature are supportive of at least some of these possibilities. For example, Krishnan, Nandy, and Puri (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 US 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.[36] However, none of these studies examine the industry dimension of banking integration 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 1.0894 while those for wage and employment respectively 0.4138 and 0.6659. First, this suggests that our estimates are consistent with one another as 0.4138 + 0.6659 = 1.0797. Second, we conclude that banking integration lead to both higher employment and wage growth in the less-specialized industries relative to the more-specialized ones.[37] Next, as and $PROD = Y/L$ this means that $\gamma_{PROD} = \gamma_{VA} - \gamma_{EMP}$. Here our estimate of our difference in growth of productivity due to banking integration is 0.6740 while that of VA and EMP is respectively 1.6907 and 0.6659. Since 1.6907 - 0.6659 = 1.0248 which means our productivity per worker growth may be underestimated. This may be due to the fact that our employment measure does not perfectly capture the actual number hours worked but the fact that we compare results without the proper lag structure as shown by AB estimators may also weigh in. Finally, since $WAGE = (1-\alpha)\ Y/L = (1-\alpha)\ PROD$ we have $\gamma_{WAGE} = \gamma_{1-\alpha} + \gamma_{PROD}$. For the U.S. the parameter α grows according

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for *K*, separating out new investments, existing capital stock and depreciation from each other would not be trivial.

[36] 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.

[37] Demyanyk, Ostergaard and Sørensen (2007) find that the personal income insurance (the ability of personal income to absorb state-level shocks) increases over the years post-interstate banking deregulations whereas Demyanyk (2008) finds that self-employed income increased over the years after interstate branching deregulations. Both studies relate their findings to the availability of more small business finance post-deregulation, but neither of them has an industry dimension.

to the Penn World Tables v.8.1 from 0.346 in years 1980-1982 to 0.361 in the years 1996-1998 which implies a 0.18% fall in (1-α) parameter yearly over the sample period. Then the obtained estimates lead us to calculate $\gamma_{1-\alpha}+\gamma_{PROD}$ = -0.18 + 0.674 = 0.494, close to our estimate for γ_{WAGE}.

6. 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, typically it is not possible to observe the industry composition of the banks' loan portfolios. Second, 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 a proper identification. Third, 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.

The US interstate bank-entry deregulations provide a series of exogenous shocks that we exploit to overcome these difficulties. The staggered state-pair interstate banking deregulations allow us to identify the effects of banking integration, as they permit instrumenting for our test variable. Because it is impossible to measure directly banks' industry expertise in lending with the macro-level data that are available to us, these sets of deregulations allow us to proxy for industry knowledge by the banks' higher exposure to certain industries in their home markets prior to entry into new markets (something that was not possible before state-pair deregulations).

We find a series of evidence that are consistent with our conjecture that stipulates that banking integration affects states' industry structures: following interstate bank-entry deregulation, as MBHCs (that were over-exposed to certain industries in which their home state is more specialized) acquired banks in other states for the first time, the resulting integration among banks led to an increase in the growth of sectors located in states that are less specialized in them compared to the growth of the same sectors in those states that are more specialized. Our evidence is based different sets of estimations (Within regressions, IV estimates, AB estimates) in some of which we also take into account the dynamic panel nature of our data. The observed effect is more accentuated in industries that are more external finance dependent.

Our results, which are robust in the series of checks that we conduct, indicate a channel through which the industrial landscape is shaped by banks' lending choices. As banking organizations make use of the information that they have accumulated in their home market when they enter the new markets (states) for the first time, the industries that were under-developed in the latter markets benefit. We do not know whether this effect is due to higher amount of sector-specific lending, or better pricing, as our data do not contain such refined information. The policy dilemma is obvious: banking regulators' decision for foreign bank entry can have implications beyond the stability of the financial system: new banks can affect industrial structure in a way that depends on their country of origin and as a result can affect sector-specific development.

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Table 1. Under- and over-specialized industries

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 US manufacturing output. An under-specialized (over-specialized) industry would have a ratio less (higher) than one.

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

Table 2. Descriptive Statistics

The data come from the BEA Regional Economic Accounts data between 1981 and 1997, which cover 48 contiguous US states (Alaska, Hawaii, and the District of Columbia are excluded) and 19 manufacturing industries at two-digit SIC level (tobacco industry is excluded). *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 US 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 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. The instrumental variable $YEARS\_SINCE_{i,j,t}$ is the sum of average number of years since the effective deregulation between each state-pair. 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 are: measures are Value Added (VA), Gross Operating Surplus (GOS), Compensation of Employees (COMP), employment (EMP), productivity (PROD) and worker remuneration (WAGE). VA is the contribution of an industry to gross state product. GOS is the surplus accrued to capital from production. COMP consists of wages, salaries and social benefits paid to employees. EMP is the wage and salary employment in the industry. PROD (=VA/EMP) is a measure of productivity. WAGE (=COMP/EMP) is a measure of compensation per worker. Superscript [a] denotes that the hypothesis that the mean of the variable is not different from zero could not be rejected at a 10% level.

$SPECIALIZATION_{i,s}$	298,690	0.59410	0.35674	0.08455	2.66082
$SPECIALIZATION_{j,s}$	298,690	1.19544	0.57939	0.09014	2.81462
$\Delta SPECIALIZATION_{i,j,s}$	298,690	0.60133	0.51414	0.00004	2.69707
$L1.DEREGULATED_{i,j,t}$	298,690	0.40575	0.49103	0	1
$L1.INTEGRATION_{i,j,t}$	298,690	0.00195	0.01118	0	0.22763
$L1.YEARS\_SINCE_{i,j,t}$	298,690	1.47357	2.47521	0	13.71370
$\Delta ln(VA_{i,s,t})$	295,647	0.05641	0 .1747	-1.44691	1.78397
$\Delta ln(VA_{j,s,t})$	295,647	0.05607	0.15605	-1.44691	1.78397
$\Delta ln(GOS_{i,s,t})$	144,211	0.07024	0.43867	-4.81218	5.24174
$\Delta ln(GOS_{j,s,t})$	144,211	0.07668	0.39452	-4.81218	5.24174
$\Delta ln(COMP_{i,s,t})$	240,516	0.04955	0.10166	-1.22377	2.01490
$\Delta ln(COMP_{j,s,t})$	240,516	0.04664	0.07989	-1.22377	2.01490
$\Delta ln(EMP_{i,s,t})$	240,567	0.00839	0.09113	-1.48160	1.74216
$\Delta ln(EMP_{j,s,t})$	240,567	0.00351	0.07190	-1.19987	1.68243
$\Delta ln(PROD_{i,s,t})$	240,567	0.04775	0.14045	-1.64686	1.77875
$\Delta ln(PROD_{j,s,t})$	240,567	0.05352	0.13099	-1.64686	1.77875
$\Delta ln(WAGE_{i,s,t})$	240,516	0.04116	0.05783	-0.64350	0.78845
$\Delta ln(WAGE_{j,s,t})$	240,516	0.04313	0.04560	-0.57367	0.6663
$\Delta ln(VA_{i,s,t}) - \Delta ln(VA_{j,s,t})$	295,647	0.00034[a]	0.21282	-2.56495	2.02401
$\Delta ln(GOS_{i,s,t}) - \Delta ln(GOS_{j,s,t})$	144,211	-0.00643	0.54408	-6.26760	7.41034
$\Delta ln(COMP_{i,s,t}) - \Delta ln(COMP_{j,s,t})$	240,516	0.00290	0.11688	-2.22034	2.08295
$\Delta ln(EMP_{i,s,t}) - \Delta ln(EMP_{j,s,t})$	240,567	0.00487	0.10252	-2.02021	1.84219
$\Delta ln(PROD_{i,s,t}) - \Delta ln(PROD_{j,s,t})$	240,567	-0.00577	0.17522	-2.20636	1.92428
$\Delta ln(WAGE_{i,s,t}) - \Delta ln(WAGE_{j,s,t})$	240,557	-0.00197	0.06423	-0.76398	0.78005

Table 3. Effect of pairwise interstate banking deregulation on differential output growth at the state-pair-sector level

This table presents *Within* regressions: $\Delta\ln(Y_{i,s,t}) - \Delta\ln(Y_{j,s,t}) = \beta\ DEREGULATED_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$ where, $\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$ 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; $DEREGULATED_{i,j,t}$ is an in 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; all regressions include state-pair-industry, state i-year, state j-year, and sector-year, and year fixed-effects. Y is one of Value Added (VA), Gross Operating Surplus (GOS), compensation of employees ($COMP$), number of employees (EMP), productivity as measured by output per employee ($PROD$), or wage measured as compensation per employee ($WAGE$). Lt represents the t^{th} lag. The standard errors are clustered at the state-pair-industry level. *t*-Stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

PANEL A: no lags						
	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.DEREGULATED	0.0118***	0.0262***	0.0062***	0.0052***	0.0059***	0.0007
	(6.28)	(4.40)	(4.92)	(4.67)	(3.71)	(1.22)
Number of observations	295,647	144,211	240,516	240,567	240,567	240,516
Number of clusters	17,391	8,483	14,148	14,151	14,151	14,148

PANEL B: with lags						
	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.DEREGULATED	0.0123***	0.0265***	0.0059***	0.0049***	0.0064***	0.0008
	(5.90)	(3.90)	(4.95)	(4.86)	(3.54)	(1.32)
L1.[$\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$]	-0.1180***	-0.2716***	0.1154***	0.1430***	-0.2264***	-0.1818***
	(35.27)	(65.06)	(30.20)	(42.30)	(74.81)	(45.67)
L2.[$\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$]	-0.0695***		-0.0419***			
	(25.01)		(11.62)			
L3.[$\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$]	-0.0844***		-0.0289***			
	(32.01)		(9.14)			
L4.[$\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$]			-0.0715***			
			(15.64)			
Number of observations	295,519	144,147	240,019	240,567	240,567	240,500
Number of clusters	17,391	8,483	141,48	14,151	14,151	14,148

Table 4. Effect of pairwise interstate banking deregulation on differential output growth with specialization difference

Panel A of this table presents *Within* regressions $\Delta\ln(Y_{i,s,t}) - \Delta\ln(Y_{j,s,t}) = \beta_1 L1.DEREGULATED_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$ using subsamples defined by the quartiles of differences in industry specializations at the state-pair level. Panel B of this table presents *Within* regressions $\Delta\ln(Y_{i,s,t}) - \Delta\ln(Y_{j,s,t}) = \beta_1 L1.DEREGULATED_{i,j,t} + \beta_2 L1.DEREGULATED_{i,j,t} \times \Delta SPECIALIZATION_{i,j,s} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$. The variables are defined as follows: $\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$ 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*; $DEREGULATED_{i,j,t}$ is an in 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; $\Delta SPECIALIZATION_{i,j,s}$ equals $|SPECIALIZATION_{i,s} - SPECIALIZATION_{j,s}|$ with *SPECIALIZATION* 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 US manufacturing output (specializations are defined as of the year of effective banking deregulation of state-pair *i-j*); all regressions include state-pair-industry, state i-year, state j-year, and sector-year, and year fixed-effects. *Y* is one of Value Added (*VA*), Gross Operating Surplus (*GOS*), compensation of employees (*COMP*), number of employees (*EMP*), productivity as measured by output per employee (*PROD*), or wage measured as compensation per employee (*WAGE*). *Lt* represents the t^{th} lag. The standard errors are clustered at the state-pair-industry level. *t*-Stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Within regressions (no lags)						
	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.DEREGULATED	0.0022	0.0185	0.0042*	0.0046**	0.0006	-0.0008
(1^{st} Quartile of *ΔSPECIALIZATION*)	(0.59)	(1.54)	(1.69)	(2.03)	(0.21)	(0.75)
L1.DEREGULATED	0.0067*	0.0373***	0.0025	0.0020	0.0063**	0.0005
(2^{nd} Quartile of *ΔSPECIALIZATION*)	(1.84)	(3.21)	(1.07)	(0.95)	(2.09)	(0.47)
L1.DEREGULATED	0.0204***	0.0316***	0.0095***	0.0093***	0.0083***	0.0001
(3^{rd} Quartile of *ΔSPECIALIZATION*)	(5.60)	(2.70)	(3.84)	(4.19)	(2.64)	(0.08)
L1.DEREGULATED	0.0180***	0.0192	0.0079***	0.0049**	0.0078**	0.0027**
(4^{th} Quartile of *ΔSPECIALIZATION*)	(4.38)	(1.60)	(2.90)	(2.08)	(2.21)	(2.25)
Panel B: Within regressions (no lags)						
	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.DEREGULATED	0.0080***	0.0268***	0.0035**	0.0023*	0.0059***	0.0010*
	(3.83)	(4.08)	(2.44)	(1.72)	(3.44)	(1.66)
L1.DEREGULATED×ΔSPECIALIZATION	0.0067***	-0.0010	0.0046***	0.0053***	-0.0000	-0.0006
	(4.27)	(0.21)	(3.38)	(4.27)	(0.02)	(1.21)

Table 5. Effect of pairwise interstate banking integration on differential output growth at the state-pair-sector level

This table presents *Instrumental Variables* (IV) regressions: $\Delta \ln(Y_{i,s,t}) - \Delta \ln(Y_{j,s,t}) = \beta\, L1.INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$ where, $\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$ 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*; $INTEGRATION_{j,t}$ is 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; all regressions include state-pair-industry, state-year, sector *s*-year, and year fixed-effects. *Y* is one of Value Added (*VA*), Gross Operating Surplus (*GOS*), compensation of employees (*COMP*), number of employees (*EMP*), productivity as measured by output per employee (*PROD*), or wage measured as compensation per employee (*WAGE*). *Lt* represents the t^{th} lag. The standard errors are clustered at the state-pair-industry level. *t*-Stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

PANEL A: no lags						
	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.INTEGRATION	0.6944***	0.4190	0.3554***	0.1878**	0.3117***	0.1525***
	(5.69)	(1.43)	(4.25)	(2.48)	(3.84)	(4.34)
Number of observations	295,647	144,211	240,516	240,567	240,567	240,516
Number of clusters	17,391	8,483	14,148	14,151	14,151	14,148

PANEL B: with lags						
	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.INTEGRATION	0.9391***	0.7600**	0.3779***	0.1475**	0.4304***	0.1802***
	(6.31)	(2.14)	(4.55)	(2.25)	(4.43)	(4.41)
L1.[$\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$]	-0.1181***	-0.2716***	0.1154***	0.1430***	-0.2264***	-0.1818***
	(35.34)	(65.31)	(30.25)	(42.39)	(74.98)	(45.79)
L2.[$\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$]	-0.0697***		-0.0419***			
	(25.10)		(11.66)			
L3.[$\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$]	-0.0846***		-0.0290***			
	(32.15)		(9.19)			
L4.[$\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$]			-0.0716***			
			(15.70)			
Number of observations	295,519	144,147	240,019	240,567	240,567	240,500
Number of clusters	17,391	8,483	141,48	14,151	14,151	14,148

Table 6. Effect of pairwise interstate banking integration on differential output growth with specialization difference

Panel A of this table presents *Instrumental Variables* (IV) regressions $\Delta \ln(Y_{i,s,t}) - \Delta \ln(Y_{j,s,t}) = \beta_1\ L1.INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$ using subsamples defined by the quartiles of differences in industry specializations at the state-pair level. Panel B of this table presents IV regressions $\Delta \ln(Y_{i,s,t}) - \Delta \ln(Y_{j,s,t}) = \beta_1\ L1.INTEGRATION_{i,j,t} + \beta_2\ L1.INTEGRATION_{i,j,t} \times \Delta SPECIALIZATION_{i,j,s} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$. Variables are defined as follows: $\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$ 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*; $INTEGRATION_{j,t}$ is 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; $\Delta SPECIALIZATION_{i,j,s}$ equals $|SPECIALIZATION_{i,s} - SPECIALIZATION_{j,s}|$ with *SPECIALIZATION* 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 US manufacturing output (specializations are defined as of the year of effective banking deregulation of state-pair *i-j*); all regressions include state-pair-industry, state *i*-year, state *j*-year, sector *s*-year, and year fixed-effects; . *Y* is one of Value Added (*VA*), Gross Operating Surplus (*GOS*), compensation of employees (*COMP*), number of employees (*EMP*), productivity as measured by output per employee (*PROD*), or wage measured as compensation per employee (*WAGE*). *Lt* represents the t[th] lag. The standard errors are clustered at the state-pair-industry level. *t*-Stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: IV regressions (no lags)

	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.INTEGRATION	0.1299	-0.1260	-0.0474	-0.1162	-0.0934	0.0189
(1st Quartile of *ΔSPECIALIZATION*)	(0.59)	(0.24)	(0.33)	(0.83)	(0.65)	(0.30)
L1.INTEGRATION	0.5315***	-0.0522	0.2853**	0.1752	0.2021	0.1089**
(2nd Quartile of *ΔSPECIALIZATION*)	(2.67)	(0.11)	(2.15)	(1.52)	(1.55)	(2.03)
L1.INTEGRATION	1.1835***	0.3862	0.7179***	0.4402***	0.6185***	0.2098***
(3rd Quartile of *ΔSPECIALIZATION*)	(4.68)	(0.69)	(4.01)	(3.22)	(3.71)	(2.98)
L1.INTEGRATION	1.6907***	2.5553**	1.0894***	0.6659**	0.6740**	0.4138***
(4th Quartile of *ΔSPECIALIZATION*)	(3.87)	(2.31)	(3.50)	(2.52)	(2.30)	(3.01)

Panel B: IV regressions (no lags)

	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.INTEGRATION	-0.6770***	-0.7500	-0.7831***	-0.8324***	-0.0415	0.0156
	(2.71)	(1.28)	(4.23)	(5.00)	(0.26)	(0.21)
L1.INTEGRATION×ΔSPECIALIZATION	3.1480***	2.7976**	2.6332***	2.3614***	0.8175**	0.3166*
	(5.76)	(2.21)	(6.44)	(6.55)	(2.45)	(1.95)

Table 7. Effect of pairwise interstate banking integration on differential output growth: High versus low external finance dependent industries

This table presents *Instrumental Variables* (IV) regressions: $\Delta \ln(Y_{i,s,t}) - \Delta \ln(Y_{j,s,t}) = \beta_1 L1.INTEGRATION_{i,j,t} + \delta_{i,j,s} + \delta_{i,t} + \delta_{j,t} + \delta_{s,t} + \delta_t + e_{i,j,s,t}$ where, $\Delta ln(Y_{i,s,t}) - \Delta ln(Y_{j,s,t})$ 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*; $INTEGRATION_{j,t}$ is 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; all regressions include state-pair-industry, state *i*-year, state *j*-year, and sector *s*-year fixed-effects. *Y* is one of Value Added (*VA*), Gross Operating Surplus (*GOS*), compensation of employees (*COMP*), number of employees (*EMP*), productivity as measured by output per employee (*PROD*), or wage measured as compensation per employee (*WAGE*). Panel A presents β_1 estimates obtained with the low-external finance dependent (EFD) sample, whereas Panel B those obtained with high-EFD, with EFD being defined as in Rajan and Zingales (1998). *Lt* represents the t^{th} lag. The standard errors are clustered at the state-pair-industry level. *t*-Stats are reported below coefficient estimates. *, **, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: IV regressions (no lags) – Low external finance dependent industries

	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.INTEGRATION	0.4211***	-0.1326	0.0391	-0.0733	0.1773*	0.1124**
	(2.71)	(0.36)	(0.35)	(0.74)	(1.66)	(2.38)

Panel A: IV regressions (no lags) – High external finance dependent industries

	VA	*GOS*	*COMP*	*EMP*	*PROD*	*WAGE*
L1.INTEGRATION	1.0031***	0.9571**	0.7347***	0.4897***	0.4894***	0.2088***
	(5.28)	(2.07)	(5.77)	(4.20)	(4.05)	(4.12)